

# Does Anticipated Information Impose a Cost on Risk-Averse Investors?

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## Abstract

This paper theoretically and empirically investigates how the risk of future adverse price changes created by the anticipated arrival of information influences risk-averse investors' trading decisions in institutionally imperfect capital markets. Specifically, I examine how trading volume is influenced by the trade-off between risk-sharing benefits of immediate trade to mitigate exposure to future adverse price changes, and explicit transaction costs imposed on such trades. Employing a stylized model, I demonstrate that current trading decisions depend upon two aspects of risk: the expected intensity of future price fluctuations per unit of time, and the duration of time that risk must be borne. Tension in the model is created by introducing an incremental capital gains tax rate applied to trading profits on shares held for less than a requisite amount of time. Thus, risk-averse investors face an economic tension between trading immediately to an optimal risk-sharing portfolio at the cost of incurring an incremental tax on realized trading profits, versus postponing trade to avoid the incremental tax while facing the risk of interim, adverse price changes. The fact that investors can reduce tax costs by postponing the sale of shares until a known, future point in time creates a unique opportunity to empirically investigate the impact of the duration of risk on trading behavior. Consistent with the model's predictions, I document that as the number of days left to avoid the incremental tax increases (i.e., duration of risk increases), trading volume around quarterly earnings announcements is less sensitive to the incremental tax on short-term trading profits. Similarly, as the expected volatility of future stock price increases (i.e., intensity increases), current trading volume is again less sensitive to incremental tax costs. These results suggest that investors are more willing to incur explicit tax costs in order to insulate themselves against increases in the risk of price fluctuations driven by increases in the duration or intensity of risk.

# 1 Introduction

In efficient capital markets, stock prices adjust to reflect the arrival of new information, which leads to stock price volatility (e.g., Beaver, 1968; Fama, 1970; Fama, 1991). Expected price volatility deriving from the *anticipated* arrival of information imposes an implicit cost upon undiversified, risk-averse investors by virtue of their exposure to the risk of adverse price changes (Hirshleifer, 1971; Verrecchia, 1982).<sup>1</sup> In response, risk-averse investors generally desire to trade shares prior to the arrival of information in order to spread the economy’s aggregate risk while diversifying their idiosyncratic risks.<sup>2</sup> In an idealized, perfect capital market with frictionless trading, investors can quickly and efficiently balance their portfolios to insure themselves against adverse price changes in the future. However, the existence of costly trading frictions can constrain investors from trading to their desired portfolios, leaving them exposed to implicit costs associated with the risk of adverse price changes from the arrival of new information.

In this paper, I theoretically and empirically investigate how trading behavior in institutionally imperfect capital markets is explicitly influenced by the risk of future adverse price changes. In particular, I examine the relationship between trading volume and the risk of adverse price changes in the presence of trading frictions created by the existence of intertemporal tax discontinuities (hereafter ITDs). An ITD results from the incremental capital gains tax rate applied to trading profits on shares held for less than a requisite amount of time.<sup>3</sup> In order to qualify for the lower long-term capital gains tax, investors are required to hold assets for a requisite amount of time (typically 12 months) before selling them, or else incur the higher short-term capital gains tax on trading profits. Given an ITD, risk averse investors face an economic tension between trading immediately to an optimal risk-sharing portfolio at the cost of incurring an incremental tax on realized trading profits, versus postponing trade to avoid the incremental tax while facing the risk of interim, adverse price changes. This tension is the focus of this paper.

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<sup>1</sup>*Ceteris paribus*, anticipated price volatility is increasing in the precision of the anticipated information.

<sup>2</sup>A prominent theoretical model of optimal risk sharing in financial markets is the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965). In the CAPM, risk-averse investors seek to minimize their exposure to the risk of adverse price changes by holding a diversified portfolio consistent with their individual preferences for risk.

<sup>3</sup>Shackelford and Verrecchia (2002) coin the term intertemporal tax discontinuity and define it as “a circumstance in which different tax rates are applied to gains realized at one point in time versus some other point in time” (pg. 205). In the context of my study, an ITD specifically refers to the difference in tax rates applied to long-term versus short-term capital gains.

I begin by developing a theoretical framework that employs a two-period model where risk-averse investors are endowed with a desire to trade for risk-sharing purposes. At date 1, where an ITD cost prevails, investors are presented with an opportunity to trade. Investors can avoid paying the ITD cost by postponing some of their desired trade until date 2 when they will have held shares sufficiently long enough to avoid paying the incremental ITD cost. However, by delaying trade, they do not achieve their optimal risk-sharing portfolio at date 1. In the interim, investors are exposed to the risk of adverse price changes due to the anticipated arrival of new information signals.<sup>4</sup> I find that period 1 trading volume is decreasing in the magnitude of the aggregate ITD cost among all investors, and increasing in the precision of the anticipated information.<sup>5</sup>

The model yields empirical implications concerning how the negative relationship between volume and ITD costs vary with the risk of future price changes. As just discussed, *ceteris paribus*, trading volume is decreasing in aggregate ITD costs among investors. However, in making their trading decision, individual investors are also concerned about the risk of adverse price changes while waiting to qualify for the lower tax rate. I demonstrate that as the precision of the anticipated information signals increases, which increases price volatility and the risk of future adverse price changes, investors place less weight on ITD incentives in making their current trading decisions. Consistent with the model, I empirically document that as price volatility increases, traders become more willing to incur the ITD cost involved with trading before satisfying the requisite ITD holding period in order to trade closer to their optimal risk-sharing portfolio and insulate themselves against anticipated price volatility.

Specifically, I find that the total amount of risk each investor considers is an increasing function of both the *intensity* and the *duration* of the risk of adverse price changes. Intuitively, *intensity* captures the risk of adverse price movements per unit of time, while *duration* captures the amount of time that such risk must be held. For example, a trader may have only a few days left in the requisite ITD holding period, but the risk of adverse price movement is very intense during

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<sup>4</sup>In the model, the risk of adverse price changes between the first and second rounds of trading is driven by the precision of the anticipated information signals. In essence, signals of high precision resolve a lot of uncertainty, which (from the ex-ante perspective of period 1) increases the risk of adverse price movements for an investor holding a sub-optimal risk-sharing portfolio. If no signals are released in the interim, there is no risk of adverse price changes and no tension exists as all investors wait to trade until the low tax rate is operative at date 2.

<sup>5</sup>That is, the risk of future adverse price changes increases in the precision of anticipated future signals, as high precision signals will cause the future price to be very sensitive to these signals, exposing risk-averse traders to the possibility of large price drops.

the short remaining interval, creating incentives for the investor to trade now towards an optimal portfolio to avoid adverse price movements. Likewise, even if intensity is low, an investor with a long duration until qualifying for the favorable long-term tax rate can still have strong incentives to trade today because the low intensity risk must be held over a long time period.

First, I empirically examine the impact of the *duration* component of risk on trading volume around quarterly earnings announcements. Employing a MIXed DATA Sampling (MIDAS) regression, I test whether the duration component of risk affects investors' trading responses to ITD costs. The MIDAS technique involves regressing low frequency data (e.g., quarterly observations) on high frequency data (e.g., daily observations). Instead of including just one aggregate ITD cost variable, I am able to include a different ITD cost for each holding period relative to qualification for the lower tax rate. This allows me to test if the sensitivity of trading volume to ITD costs decreases as the number of days to qualification increases (i.e., *duration* increases). I provide evidence consistent with this prediction. Second, using the average daily stock return volatility as a proxy for the *intensity* of risk, I find evidence that the sensitivity of trading volume to ITD costs decreases as the risk of adverse price changes per unit of time increases (i.e., *intensity* increases). In other words, the higher the anticipated price volatility, the less influential ITD incentives are on current trading decisions as investors become more willing to trade now to hedge the more intense risk, despite incurring higher tax costs.

A number of institutional constraints exist that may inhibit investors' ability to optimally make trades. These include incomplete capital markets (Merton, 1987), short sale constraints/prohibitions (Diamond and Verrecchia, 1987), bid/ask spreads (Constantinides, 1986), and taxes (Shackelford and Verrecchia, 2002). While each of these transaction costs is potentially important, I choose to examine the trading friction created by the incremental ITD tax because it offers several important advantages over other transaction costs.

First, and most importantly, an ITD is a time-varying transaction cost with a finite amount of time until expiration, which is perfectly anticipated by investors. In order to qualify for the lower long-term capital gains tax rate, investors are required to hold assets for a requisite amount of time.<sup>6</sup> This is crucial for my empirical tests because it allows me to measure the time horizon over which

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<sup>6</sup>Historically, the requisite holding period has been 6, 9, 12, and 18 months. The ITD holding period of 12 months is the most common.

investors will consider the risk of adverse price changes when considering how many shares to trade in order to avoid paying an ITD transaction cost. In contrast, most other transaction costs, such as bid-ask spreads and long-term capital gains taxes, do not have an anticipated time variation that allow investors to optimally avoid them.<sup>7</sup> For example, investors can avoid paying long-term capital gains taxes by postponing the sale of their portfolio until death. However, investors' expectations over their life expectancy is unobservable.

Second, an ITD represents a potentially significant trading cost to investors. Currently, the maximum ITD cost imposed on investors, equal to the difference in the maximum statutory capital gains tax rates applied to short-term and long-term gains, is 20%, but has historically been as low as 0% (1988 – 1990) and as high as 30% (1982 – 1986). However, the actual ITD cost that investors consider may differ for a number of reasons. First, some investors may have held shares for the requisite amount of time and qualified for the lower long-term capital gains tax rate. These investors have no ITD incentive to postpone trading. Second, a portion of any short-term capital gains accrued in one security may be partially offset by short-term capital losses from another security in an investor's portfolio, leading to a lower ITD incentive to postpone trades. Third, some investors, such as institutions, may be tax-exempt.<sup>8</sup> All of these effects imply that ITD may not be important to investors and may work against finding empirical results.

Finally, recent empirical evidence supports an important role for ITD costs in shaping investor demand and trading volume. For example, Blouin, Raedy and Shackelford (2003) and Hurtt and Seida (2004) find a negative and statistically significant association between ITD costs and trading volume following quarterly earnings announcements. Reese (1998) finds similar evidence using a sample of IPO firms. However, none of these studies considers how anticipated information influences this negative relationship which is the central focus of my paper.

Examining how trading decisions are influenced by the trade-off between implicit risk costs and explicit ITD costs contributes to at least two distinct strands of literature. First, it contributes to a large body of literature, dating back at least to Hirshleifer (1971), that theoretically examines the welfare implications of anticipated information. Hirshleifer (1971) demonstrates that in a pure

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<sup>7</sup>While the magnitude of bid-ask spreads and long-term capital gain tax rates can change over time, the change is not fully anticipated (except in unusual circumstances) and thus does not provide investors with an incentive known in advance of the event.

<sup>8</sup>See Shackelford and Shevlin (2001) and Blouin, Raedy and Shackelford (2003) for a comprehensive review of why capital gain taxes may not matter to investors.

exchange economy, risk-averse investors are collectively made worse off (in expectation) if they are not allowed to contract (or trade) prior to the release of anticipated information. Trading spreads investors' risks across the economy and protects investors against the risk that the anticipated information will adversely change prices. Verrecchia (2001) refers to this as the adverse risk-sharing effect of increased disclosure.<sup>9</sup> My analysis provides a novel and powerful setting in which to directly examine the empirical implications of the adverse risk-sharing effect of anticipated information.

Second, this study contributes to a large body of tax-related literature that examines if capital markets are influenced by shareholder taxes.<sup>10</sup> Specifically, it provides discriminating predictions, based on the risk of adverse price changes, about whether investors' trading decisions are influenced by shareholder capital gain taxes. Maydew (2001) describes the need for tax-related predictions related to economic trade-offs by posing the following question: if chickens cross the road "because taxes are lower on the other side... why did not *all* the chickens cross the road?" My study argues that some chickens may choose not to cross the road to the lower tax side (i.e., wait until qualifying for the lower long-term tax rate) because the road is too wide (i.e., high *duration*), too heavily traveled (i.e., high *intensity*), or both, making it too risky to cross to the other side.

The rest of this paper is organized as follows. Section 2 outlines the theoretical framework and empirical implications. Section 3 describes the empirical sample and variable definitions. Section 4 presents the empirical analysis and results. Section 5 concludes.

## 2 Theoretical Framework

### 2.1 Assumptions

The following analysis employs a model of pure exchange populated by a countably infinite number of risk-averse investors with homogenous risk preferences. There are four discrete time periods, referred to as periods 0, 1, 2, and 3. Investors are endowed with shares of a risky asset and a risk-free bond in period 0, trade shares of both in periods 1 and 2, and consume wealth in period 3. One share of the bond (the numeraire commodity) pays one unit of consumption in period 3,

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<sup>9</sup>Subsequent studies formalize Hirshleifer's argument (e.g., Marshall, 1974; Hakansson, Kunkel and Ohlson, 1982) and develop theoretical models that examine the welfare role of anticipated information using alternative assumptions and settings. See Verrecchia (1982), Diamond (1985), Bushman (1991), Alles and Lundholm (1993), and Campbell (2004), among others. Verrecchia (2001; Section 4) provides an extensive review of this literature.

<sup>10</sup>See Shackelford and Shevlin (2001) for a comprehensive review of this literature.

while the payoff from a share of the risky asset is a random variable,  $\tilde{u}$ . The per-capita supply of the risky asset,  $x$ , is common knowledge among investors and remains fixed across all time periods.

In period 0, there are three distinct groups of investors, indexed by  $i \in \{B, S_1, S_2\} \equiv \{\text{Buyers}, \text{Sellers}_1, \text{Sellers}_2\}$ , that differ only in their risk-free bond endowment,  $E_i$ , risky asset endowment,  $D_{0,i}$ , and basis,  $P_{0,i}$ . Specifically, *Buyers* are endowed with a sufficiently “underweighted” amount of the risky asset (i.e.,  $D_{0,B} < x$ ), and therefore wish to buy additional shares. Conversely, *Sellers*<sub>1</sub> and *Sellers*<sub>2</sub>, with equal endowments, are sufficiently “overweighted” (i.e.,  $D_{0,S_1} = D_{0,S_2} > x$ ), and therefore wish to sell a portion of their risky asset portfolio.<sup>11</sup> In addition, each investor  $i$  is endowed with a basis,  $P_{0,i} \in \{P_{0,B}, P_{0,S_1}, P_{0,S_2}\}$ , used to compute capital gains. Finally, let  $\theta\delta$ ,  $\theta(1 - \delta)$ , and  $(1 - \theta)$  represent the relative proportions of *Sellers*<sub>1</sub>, *Sellers*<sub>2</sub>, and *Buyers* in the economy, respectively, which is fixed across time. Therefore, in every period  $t$ , per-capita demand for the risky asset must equal per-capita supply:  $\theta[\delta D_{t,S_1} + (1 - \delta) D_{t,S_2}] + (1 - \theta) D_{t,B} = x$ . This identity implies that the aggregate *change* in demand across any number of time periods,  $r$ , is equal to zero:

$$\theta[\delta(D_{t,S_1} - D_{t-r,S_1}) + (1 - \delta)(D_{t,S_2} - D_{t-r,S_2})] + (1 - \theta)(D_{t,B} - D_{t-r,B}) = 0, \quad (1)$$

where  $D_{t,i}$  is investor  $i$ 's demand for the risky asset in period  $t$ .

In period 1, all traders observe an earnings announcement about the value of the risky asset. Conditional upon this announcement, investors' expectations about  $\tilde{u}$  are that it has a normal distribution with a mean of  $\bar{u}$  and a precision (inverse of variance) of  $h$ .<sup>12</sup> After observing the earnings announcement, investors trade shares of the risky asset and risk-free bond at competitive prices.

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<sup>11</sup>The assumption that investors hold less than an optimal risk sharing amount is made to generate trading volume that triggers capital gains taxes. In this model, there are two situations in which no trade results. First, investors will not trade if they are endowed with an optimal risk-sharing amount of the risky asset,  $x$  (Milgrom and Stokey, 1982). Second, even if investors are given sub-optimal risk-sharing endowments, they may not trade if their initial allocations are sufficiently close to optimal risk sharing such that the marginal ITD cost is higher than the marginal risk-sharing benefit of trading the first share. I avoid this uninteresting scenario, by assuming that investors are ‘sufficiently’ overweighted and underweighted in the risky asset. Therefore, my model is intended to shed light on how anticipated information incrementally influences trading volume, *given a desire to trade*, and is not intended to explain *why* trading volume exists.

<sup>12</sup>Following Shackelford and Verrecchia (2002) I interpret this assumption as the earnings announcement subsuming all investors' prior information about  $\bar{u}$ . That is, any prior information is a forecast of the earnings announcement, which the actual earnings announcement in period 1 subsumes (for example, see Abarbanell, Lanen and Verrecchia, 1995).

Investors' period 1 demand functions are driven by two opposing forces. First, following Shackleford and Verrecchia (2002), I assume periods 0 and 1 are sufficiently close in time so that any trading profits from the sale of assets in period 1 are taxed at an unfavorable short-term capital gains tax rate,  $\tau$ . Investors can reduce their taxes by postponing their trading activity until period 2, when a second round of trade opens. I assume period 2 is sufficiently distant in time from period 1 so that any realized trading profits in this period qualify for a favorable long-term capital gains tax, which is normalized to zero. Therefore,  $\tau$  represents the spread between the short-term and long-term capital gains tax rates and captures the incremental incentive created by an ITD to postpone trading until period 2.

Second, between periods 1 and 2, investors observe  $N$  anticipated public signals,  $\tilde{y}_n = \tilde{u} + \tilde{\varepsilon}_n$  indexed by  $n \in (1, \dots, N)$ , where  $\tilde{\varepsilon}_n$  is independently and normally distributed with mean 0 and precision  $s$ . The total information contained in these signals creates an incentive for investors to trade in period 1 to protect themselves from adverse price changes in period 2.

The model concludes in period 3 when investors realize the payoff of the risky asset, pay any capital gains taxes, and consume their remaining wealth. Investors are risk averse with a utility for wealth characterized by the negative exponential utility function,  $U(\tilde{W}_i) = -\exp(-\tilde{W}_i/\gamma)$ , where  $\gamma$  is a risk tolerance parameter common to all investors.  $\tilde{W}_i$  is investor  $i$ 's final wealth that is equal to:

$$\begin{aligned} \tilde{W}_i = & E_i + P_{0,i}D_{0,i} + (P_1 - P_{0,i})(D_{0,i} - D_{1,i}) + (P_2 - P_{0,i})(D_{1,i} - D_{2,i}) \\ & + (\tilde{u} - P_{0,i})D_{2,i} - \tau_i(P_1 - P_{0,i})(D_{0,i} - D_{1,i}), \end{aligned} \quad (2)$$

where  $P_1$  and  $P_2$  are the prices of the risky asset and  $D_{1,i}$  and  $D_{2,i}$  are investor  $i$ 's demand for the risky asset in periods 1 and 2, respectively. The final term in (2) reflects the total amount of capital gains taxes paid by investor  $i$  on trading profits in period 1.

## 2.2 Model Equilibrium

The equilibrium price and demand functions in periods 1 and 2 are solved using backward induction. In period 2, trader  $i$  maximizes his expected utility with respect to his demand for the risky asset,  $D_{2,i}$ , conditional upon observing the earnings announcement and the  $N$  intermediate public signals.

Because investor  $i$ 's period 1 tax,  $\tau_i$ , does not affect this optimization problem, it is straightforward to solve for the equilibrium in period 2:

$$\begin{aligned}\tilde{P}_2 &= E[\tilde{u}|\tilde{y}_1, \dots, \tilde{y}_N] - \frac{x}{\gamma} \text{Var}[\tilde{u}|\tilde{y}_1, \dots, \tilde{y}_N] \\ &= \frac{h\bar{u} + s \sum_{n=1}^N \tilde{y}_n}{h + Ns} - \frac{x}{\gamma(h + Ns)},\end{aligned}\tag{3}$$

$$D_{2,i} = x, \quad \forall i.\tag{4}$$

Equations (3) and (4) are a standard result for a model of this type in which all information is public and investors have homogenous risk preferences (e.g., Verrecchia, 1982). Each investor, regardless of type, holds a share of the risky asset equal to the per-capita supply,  $x$ . This demonstrates that even in the presence of an ITD, investors do eventually achieve an optimal risk sharing portfolio prior to the realization of the risky asset payoff. In contrast, investors in the one-period ITD model of Shackelford and Verrecchia (2002) never reach such an optimal risk sharing portfolio.

In period 1, trader  $i$  chooses his demand,  $D_{1,i}$ , which maximizes his expected utility given (3) and (4), while anticipating the release of  $N$  public signals before period 2. As derived in Appendix A, the equilibrium price and demand functions are described in the following Lemma:

**Lemma 1** *In the presence of an ITD, the (unique) period 1 equilibrium following a “good news” earnings announcement (i.e.,  $P_1 > P_{0,i}, \forall i$ ) is one in which Buyers (Sellers) always buy (sell) shares of the risky asset. That is,*

$$P_1 = \frac{\bar{u} - \frac{x}{\gamma h} - \theta\tau\bar{P}_0}{(1 - \theta\tau)},\tag{5}$$

$$x \leq D_{1,S_1} = x + \frac{\gamma h \left(1 + \frac{h}{Ns}\right) \tau (1 - \theta) \left[\bar{u} - \frac{x}{\gamma h} - \frac{(1 - \theta\tau)}{(1 - \theta)} P_{0,S_1} - \tau\bar{P}_0\right]}{(1 - \theta\tau)} \leq D_{0,S_1},\tag{6}$$

$$x \leq D_{1,S_2} = x + \frac{\gamma h \left(1 + \frac{h}{Ns}\right) \tau (1 - \theta) \left[\bar{u} - \frac{x}{\gamma h} - \frac{(1 - \theta\tau)}{(1 - \theta)} P_{0,S_2} - \tau\bar{P}_0\right]}{(1 - \theta\tau)} \leq D_{0,S_2},\tag{7}$$

$$D_{0,B} \leq D_{1,B} = x - \frac{\gamma h \left(1 + \frac{h}{Ns}\right) \theta\tau \left[\bar{u} - \frac{x}{\gamma h} - \bar{P}_0\right]}{(1 - \theta\tau)} \leq x,\tag{8}$$

where  $\bar{P}_0 = \delta P_{0,S_1} + (1 - \delta) P_{0,S_2}$  is the average tax basis among investors selling shares of the risky asset.

Equation (5) illustrates that the presence of the ITD increases stock price as *Sellers* demand

compensation for incurring the incremental tax in period 1.<sup>13</sup> In equilibrium, the price reflects the average tax rate,  $\theta\tau$ , among all investors as the total tax cost in the economy is redistributed across all investors. Therefore, while *Buyers* are not explicitly taxed on the purchase of shares in period 1, they are implicitly taxed through an increase in the price of the risky asset. Surprisingly, equation (5) does not depend upon any characteristics of the anticipated public signals (i.e.,  $N$  and  $s$ ). In fact, this result is identical to the price derived in the one-period model of Shackelford and Verrecchia (2002), which does not allow a role for intermediate public signals.

In contrast to price, the individual demand functions in (6), (7), and (8) depend upon  $N$  and  $s$  as well as the average ITD,  $\theta\tau$ , among all investors. In equilibrium, investors' optimal demand falls somewhere in between their initial endowment,  $D_{0,i}$  and their optimal risk sharing allocation,  $x$ . How closely each investor trades to  $x$  depends upon the relative costs from anticipated signal characteristics (i.e.,  $N$  and  $s$ ), compared to the explicit and implicit ITD costs.

At one extreme, when the anticipated signals provide no additional information (i.e.,  $N \rightarrow 0$  or  $s \rightarrow 0$ ), investors know exactly what the price in period 2 will be since there will be no new information to update their beliefs about the underlying value of the risky asset. Consequently, investors will not trade away from their endowment position,  $D_{0,i}$ , because they can avoid paying the ITD without any risk of adverse price changes.

At the other extreme, when the anticipated signals are expected to fully reveal the payoff of the risky asset (i.e.,  $N \rightarrow \infty$  or  $s \rightarrow \infty$ ), investors trade as close as possible to the optimal risk sharing allocation,  $x$ . By allowing  $N$  or  $s$  to go to  $\infty$ , my model effectively collapses to the one-period model of Shackelford and Verrecchia (2002) and (6), (7), and (8) are identical to the demand functions derived in that paper's model.

The intention of the model developed in Shackelford and Verrecchia (2002) is to examine how the existence of an ITD influences price and trading volume, holding the precision of the anticipated information environment constant at  $\infty$ . In contrast, the intention of my model is to examine how changing the precision of the anticipated information environment influences price and trading volume when an ITD is present.

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<sup>13</sup>The situation where *Sellers* demand compensation from *Buyers* for the capital gain taxes paid on trades is commonly referred to as the "lock-in" effect (e.g., Landsman and Shackelford, 1995; Klein, 1999; Jin, 2006; Dai et al., 2008).

### 2.3 Period 1 Trading Volume

The results from Lemma 1 highlight how anticipated public signals influence individual demand, but not price, when ITDs are present. Thus, the key construct underlying my model's empirical predictions is the function describing the period 1 trading volume following the earnings announcement. By definition, the per-capita trading volume in period 1 is equal to

$$\begin{aligned}
V_1 &= \frac{1}{2} \int |D_{1,i} - D_{0,i}| di \\
&= \frac{1}{2} \theta [\delta |D_{1,S_1} - D_{0,S_1}| + (1 - \delta) |D_{1,S_2} - D_{0,S_2}|] \\
&\quad + \frac{1}{2} (1 - \theta) |D_{1,B} - D_{0,B}| \\
&= \frac{1}{2} \theta [\delta (D_{0,S_1} - D_{1,S_1}) + (1 - \delta) (D_{0,S_2} - D_{1,S_2})] \\
&\quad + \frac{1}{2} (1 - \theta) (D_{1,B} - D_{0,B}), \tag{9}
\end{aligned}$$

where the last step follows from Lemma 1, which states that *Buyers* always buy ( $D_{0,B} \leq D_{1,B}$ ) and *Sellers* always sell ( $D_{0,S_1} \geq D_{1,S_1}$  and  $D_{0,S_2} \geq D_{1,S_2}$ ). Substituting (1) into (9), per-capita trading volume is expressed in terms of *Buyers* demand:

$$V_1 = (1 - \theta) (D_{1,B} - D_{0,B}). \tag{10}$$

Finally, substituting the period 1 demand function of *Buyers* from (8) into (10) leads to the following proposition, which illustrates how trading volume is influenced by the interaction between anticipated information and ITDs:

**Proposition 1** *In the presence of an ITD, per-capita trading volume following a “good news” earnings announcement (i.e.,  $P_1 > P_{0,i}, \forall i$ ) is*

$$V_I = V^* - (1 - \theta) \frac{\overbrace{\theta \tau \bar{\Delta} P_1}^{\text{ITD incentive to postpone trade}}}{\underbrace{\frac{1}{\gamma} \text{Var}[\tilde{P}_2]}_{\text{risk incentive to trade immediately}}}, \tag{11}$$

where  $V^* = (1 - \theta) (x - D_{0,B})$  is the optimal trading volume,  $\text{Var}[\tilde{P}_2] = \frac{Ns}{h(h+Ns)}$  is the variance of period 2 price, and  $\bar{\Delta} P_1 = P_1 - \delta P_{0,S_1} - (1 - \delta) P_{0,S_2}$  is the average trading profit among *Sellers*.

Equation (11) illustrates the key tension of the model. Actual trading volume,  $V_1$ , is less than optimal risk sharing volume,  $V^*$ , by an amount proportional to the ratio of the aggregate ITD cost to the risk of an adverse price change in period 2. Specifically, as the ITD cost of trading in period 1 increases, investors trade less because the implicit cost from bearing the risk of adverse price changes becomes relatively lower than the increasing ITD cost. That is:

**Corollary 1** *Following a “good news” earnings announcement (i.e.,  $P_1 > P_{0,i}, \forall i$ ), per-capita trading volume is (weakly) decreasing in the ITD incentive to postpone trading among all investors,*

$$\frac{\partial V_1}{\partial (ITD)} = -\frac{(1-\theta)}{\frac{1}{\gamma} \text{Var}[\tilde{P}_2]} \leq 0,$$

where  $ITD = \theta\tau\bar{\Delta}P_1$ .

Corollary 1 is the main result derived in Shackelford and Verrecchia (2002), but represents a point of departure for the implications of my model. Equation (11) also demonstrates that trading volume increases as the risk incentive to trade increases. This leads to the following:

**Corollary 2** *Following a “good news” earnings announcement (i.e.,  $P_1 > P_{0,i}, \forall i$ ), the negative relationship between per-capita trading volume and the ITD incentive among all investors is (weakly) increasing (i.e., becoming less negative) in both the intensity,  $s$ , and the duration,  $N$ , of anticipated information:*

$$\frac{\partial^2 V_1}{\partial (ITD) \partial N} = \frac{\partial^2 V_1}{\partial (ITD) \partial \text{Var}[\tilde{P}_2]} \frac{\partial \text{Var}[\tilde{P}_2]}{\partial N} = (+)(+) \geq 0, \quad (12)$$

$$\frac{\partial^2 V_1}{\partial (ITD) \partial s} = \frac{\partial^2 V_1}{\partial (ITD) \partial \text{Var}[\tilde{P}_2]} \frac{\partial \text{Var}[\tilde{P}_2]}{\partial s} = (+)(+) \geq 0. \quad (13)$$

However, before proceeding, it is important to note that optimal trading volume,  $V^*$ , in equation (11) is a constant that represents the average difference between investors’ endowment and the optimal risk sharing allocation,  $x$ . If the average ITD,  $\theta\tau$ , among investors in the risky asset is equal to zero, then trading volume in period 1,  $V_1$ , will equal a constant,  $V^*$ , as investors trade without cost to an optimal risk sharing portfolio to perfectly insure themselves against adverse price changes in period 2. In this case, trading volume is not sensitive to any characteristics of the economy, and in particular those of the anticipated public signals,  $N$  and  $s$ . Therefore, the following is a necessary condition for deriving implications for trading volume:

**Necessary Condition** *A positive fraction of investors,  $0 < \theta \leq 1$ , must be subject to an ITD,  $\tau > 0$ , in period 1.*<sup>14</sup>

I turn now to a discussion of these results and the empirical implications drawn from them.

## 2.4 Empirical Implications

This section describes the main empirical implications of the model that I test in Section 4. First, recall from (11) in Proposition 1 that per-capita trading volume following an earnings announcement is given by:

$$V_1 = V^* - (1 - \theta) \frac{\overbrace{\theta\tau\bar{\Delta}P_1}^{\text{ITD incentive to postpone trade}}}{\underbrace{\frac{1}{\gamma}\text{Var}[\tilde{P}_2]}_{\text{risk incentive to trade immediately}}}. \quad (11)$$

This illustrates that per-capita trading volume following an earnings announcement is decreasing in the aggregate ITD incentive to postpone trading,  $\theta\tau\bar{\Delta}P_1$ , holding the variance of future price constant (see Corollary 1). Note that the ITD incentive depends upon the average price appreciation of the stock held by the sellers,  $\bar{\Delta}P_1$ , capturing the importance of considering aggregate incentives among all investors in determining the effects of ITDs on trading volume. Investors purchase shares at different times and with different tax bases, so that at a given point in time investors face different ITD tax incentives reflecting differences in asset appreciation.

Referring again to equation (11) in Proposition 1, we see that per-capita trading volume is increasing in the variance of future price,  $\text{Var}[\tilde{P}_2]$ , holding the ITD incentive,  $\theta\tau\bar{\Delta}P_1$ , constant. In deciding whether to postpone trade in order to minimize taxes, investors must also consider the cost of being undiversified until they qualify for the lower tax rate. As (11) shows, *ceteris paribus*, traders are more likely to trade early (i.e., period 1 trading volume increases) as the cost of being undiversified, captured by the variance of future price, increases. I disaggregate the total risk faced by investors into the *duration* ( $N$  in the model) and the *intensity* ( $s$  in the model) of risk.<sup>15</sup> Intuitively, *duration* captures the amount of time that the risk must be held until qualification for the lower rate, while *intensity* captures the risk of adverse price movement per unit of time.

<sup>14</sup>In other words, taxes matter to some investors!

<sup>15</sup>Intensity is captured by signal precision,  $s$ , in the model, as high-precision signals will cause the future price to be very sensitive to these signals, exposing risk-averse traders to the possibility of large price drops.

Both effects, based on the cross-partial derivatives of Corollary 2, lead to the two main empirical implications of the model. The first empirical implication relates the *duration* component of risk and is stated as follows:

**Empirical Implication 1** *The negative impact of ITD costs on trading volume around earnings announcements is mitigated (i.e., is less negative) as the time to qualification increases (i.e., duration increases).*

As the time to qualification increases, an investor must remain exposed to the risk of adverse price movements over a longer period. Therefore, investors optimally trade more shares today to reduce risk, despite the negative wealth effect of paying the higher short-term tax rate on trading profits.

**Empirical Implication 2** *The negative impact of ITD costs on trading volume around earnings announcements is mitigated (i.e., less negative) as the intensity of risk per unit of time increases.*

As the intensity of risk per unit of time increases (captured by the precision of a single information signal,  $s$ , in the interim period), investors are again more willing to trade early, despite the higher taxes, to insulate themselves against the higher implicit costs associated with the risk of adverse price changes. Next, I turn to the empirical analysis built around these two empirical implications.

### 3 Empirical Sample and Variable Definitions

#### 3.1 Sample Selection

To test the empirical implications of my model, I examine abnormal trading volume around quarterly earnings announcements. While quarterly earnings announcements are not an inherent aspect of my model, such a setting does provide at least two benefits. First, quarterly earnings announcements provide a large sample setting associated with spikes in trading volume (e.g., Beaver, 1968; Morse, 1981; Bamber, 1986; Landsman and Maydew, 2002). As a result, quarterly earnings announcements are likely to satisfy the theoretical criterion of “given that investors desire to trade.” Such announcements are associated with extensive portfolio rebalancing, and so provide a relatively powerful setting to detect whether risk and ITD incentives interact to influence trading volume in a manner predicted by my model.

In addition, as described in the theoretical framework, a necessary condition for a relationship to exist between risk and trading volume is that ITD incentives have to influence investors' trading decisions.<sup>16</sup> Consistent with this necessary condition, Blouin, Raedy and Shackelford (2003) and Hurtt and Seida (2004) document evidence of a negative and significant relationship between ITDs and trading volume around quarterly earnings announcements. This provides *prima facie* motivation for examining the role of risk and trading volume around quarterly earnings announcements given this prior empirical support of the necessary condition.

I begin by collecting data on all firms with an available quarterly earnings announcement date between 1982 and 2005, as found in Compustat. Next, I eliminate observations with a quarterly earnings announcement falling on a date when the requisite ITD holding period is not equal to 12 months.<sup>17</sup> Finally, I require that each observation has the necessary data from Compustat, CRSP, I/B/E/S, and Thomson Financial to compute all variables used in the empirical analysis. The final sample contains 67,493 quarterly earnings announcement observations, representing 5,903 unique firms.

### 3.2 Variable Definitions

The empirical implications developed in Section 2 rely upon three important measures: (1) trading volume (the outcome or dependent variable), (2) the ITD incentive to postpone trading, and (3) the risk incentive to trade immediately. The following describes the empirical proxies for each of the three key measures as well as other control variables used in the empirical analysis.

First, the dependent variable employed in multivariate tests is the cumulative, three-day abnormal trading volume, *AVOL*, around quarterly earnings announcements. Following Ajinkya and Jain (1989), daily abnormal trading volume is estimated as the residual from the following "market" model regression for volume:

$$V_{j,t-k} = A + B \cdot V_{m,t-k} + e_{j,t-k}, \quad (14)$$

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<sup>16</sup> Absent any transaction costs, such as an ITD, traders will immediately trade to their optimal risk sharing portfolio to insulate themselves from future adverse price changes. In other words, investors will trade to the same portfolio regardless of the risk of future adverse price changes, implying that there is no relationship between trading volume and risk. A necessary condition for such a relationship is the existence of a market friction, such as an ITD.

<sup>17</sup> This filter excludes announcements made from June 23, 1985 through July 1, 1988 (6-month holding period) and between July 29, 1997 and December 31, 1997 (18-month holding period).

$$\begin{aligned}
\text{where } V_{j,t-k} &= \frac{\ln(1.0 + \text{dollar value of firm } j\text{'s shares traded on day } t-k)}{\ln(1.0 + \text{market value of firm } j\text{'s shares outstanding on day } t-k)}, \\
V_{m,t-k} &= \frac{\ln(1.0 + \text{dollar value of shares of all stocks traded on day } t-k)}{\ln(1.0 + \text{market value of shares outstanding of all stocks on day } t-k)}, \\
e_{j,t-k} &= \text{abnormal trading volume for stock } j \text{ on day } t-k.
\end{aligned}$$

For each firm  $j$  and quarterly earnings announcement date  $t$ , coefficients  $A$  and  $B$  are estimated using daily volume observations from the 100 trading days immediately preceding day  $t - 1$  (after excluding three-day windows around prior quarterly earnings announcement dates). As prescribed by Ajinkya and Jain (1989), (14) is estimated using Estimated Generalized Least Squares (EGLS) with an AR(1) structure imposed upon the residuals to account for potential autocorrelation.<sup>18</sup> The three-day abnormal trading volume,  $AVOL$ , is defined as 100 times the cumulative daily prediction errors from (14), estimated for days  $t - 1$  to  $t + 1$  surrounding the earnings announcement date.

Second, I construct an empirical proxy for the total ITD incentive,  $ITD$ , aggregated across all investors at the earnings announcement. Recall from the theoretical framework that an individual investor's ITD incentive to postpone trading is a product of the difference between the short-term and long-term capital gains tax rates,  $\Delta RATE$ , and the change in stock price,  $\Delta P_n$ , from the time the shares were acquired to the date of the earnings announcement. Following prior ITD studies, I define  $\Delta RATE$  as the maximum statutory short-term capital gains tax rate less the maximum statutory long-term capital gains tax rate on day  $t$ .

The change in stock price at the announcement date is defined as the logarithm of the closing stock price on day  $t - 2$ ,  $\ln(P_{t-2})$ , minus the logarithm of the initial purchase price (adjusted for stock splits and stock dividends) on day  $t - n$ ,  $\ln(P_{t-n})$ , where  $n$  is the number of trading days prior to the earnings announcement on which the asset was purchased. As my model clearly demonstrates, trading volume should reflect the aggregate ITD incentive and, therefore, the aggregate price change among all investors on day  $t$ . Before aggregating price changes, it is important to note that a change in price with respect to a given day in the past may not induce a strong ITD effect on abnormal

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<sup>18</sup>Autocorrelations in trading volume could arise when all the traders do not trade within one day based on information they use to rebalance their portfolios. Using theoretical models developed by Karpoff (1986) and Huffman (1987) as motivation, Ajinkya and Jain (1989) empirically document significant autocorrelation in both raw and abnormal daily trading volume. The EGLS model takes this autocorrelation structure in the residuals into account. The first step in the EGLS regression is to estimate OLS residuals. Autocorrelations are estimated from the OLS residuals and then incorporated into a second stage regression to obtain more efficient parameter estimates (Judge et al., 1985; Kennedy, 2003). The mean OLS residual autocorrelation (untabulated) in my sample is 0.173.

trading volume around the earnings announcement if relatively few shares were traded on that particular day. In other words, if very few shares transacted on day  $t - n$ , then there is a low probability that an investor, trading at the earnings announcement date, purchased shares at  $t - n$ . The price change computed for this day should receive a lower weight than a trading day with high volume when constructing an aggregate price change measure.<sup>19</sup> Therefore, I compute a volume-weighted, average price change  $\bar{\Delta}P$  over the 248 trading days (i.e., within the requisite holding period,  $n \in [3, 4, \dots, 250]$ ) immediately preceding  $t - 1$  as follows,

$$\bar{\Delta}P = \sum_{n=3}^{250} \Delta P_n = \frac{1}{248} \sum_{n=3}^{250} \left[ \frac{dVOL_{t-n}}{\sum_{m=3}^{500} dVOL_{t-m}} \right] [\ln(P_{t-2}) - \ln(P_{t-n})],$$

where  $\Delta P_n$  is the daily volume-weighted change in price from  $t - n$  to  $t - 2$ ,  $dVOL_{t-n}$  is the raw (not abnormal) daily trading volume on day  $t - n$ , and  $\sum_{m=3}^{500} dVOL_{t-m}$  is the firm's cumulative trading volume over the two years immediately preceding the earnings announcement. Weighting the daily trading volume with respect to the two-year trading volume means that the sum of the daily weight applied to days  $t - 250$  to  $t - 3$  will be less than one. This is intended to capture the fraction of traders that have already held shares for more than one year and are no longer subject to an ITD.<sup>20</sup> The aggregate ITD incentive to postpone trading,  $ITD$ , is estimated as the product of  $\Delta RATE$  and  $\bar{\Delta}P$ .

Third, I consider empirical proxies for the total amount of risk each investor considers. The total risk is an increasing function of both the *intensity* and the *duration* of the anticipated price volatility. The *duration* component represents the amount of time over which a given risk *intensity* must be held. It is defined as the number of trading days an investor, who purchased shares on day  $t - n$ , has remaining until qualification for the lower tax rate. Specifically, *duration*,  $d$ , is equal to  $250 - n$  and is expressed in number of trading days.<sup>21</sup> Consequently, within a single observation,  $d$

<sup>19</sup>The volume traded on a past date will not necessarily be held up to or traded on the earnings announcement date. This makes past daily volumes a noisy proxy for the cross-section of investors trading around the earnings announcement.

<sup>20</sup>For example, consider an earnings announcement observation where the firm's total trading volume over the prior 24 months is 400,000 shares. If only 100,000 shares were traded in the most recent 12 months, then the estimate of  $\bar{\Delta}P$  for this observation receives a total weight of 1/4 (or 100,000/400,000). This assumes that 25% of investors trading at the earnings announcement date are potentially subject to an ITD at the earnings announcement. Conversely, if 300,000 of the 400,000 shares were traded in the most recent 12-month period, then the estimate of  $\bar{\Delta}P$  for this observation receives a total weight of 3/4, or three times the weight of the other observation. Inferences do not change when cumulative three-year and five-year trading volume are used instead.

<sup>21</sup>This definition is a direct result of constraining my sample to time periods with a one-year (or approximately 250

will vary among investors depending on the number of trading days,  $n$ , prior to the announcement date that each investor purchased shares. The *intensity* component represents the risk of adverse price changes per unit of time (e.g., per trading day). Guided by the predictions of my model, I define *INTENSITY* as the variance of firm-specific daily stock returns in excess of the risk-free rate estimated over the 100 trading days immediately preceding day  $t - 1$ .<sup>22</sup>

In addition, I also control for the influence of several factors that prior empirical research has found to be associated with abnormal trading volume around quarterly earnings announcements. The absolute value of unexpected earnings, *AUE*, is intended to control for the information made available at the earnings announcement (Bamber, 1987). *AUE* is equal to the absolute value of actual quarterly earnings per share announced on day  $t$ , minus the median analyst forecasts reported by IBES over the 60 trading days prior to day  $t - 1$ , scaled by the stock price per share at the end of the fiscal quarter preceding the announcement. In addition, I include the square of unexpected earnings, *NONLINEAR*, to capture any nonlinearities (e.g., Freeman and Tse, 1992; Hurtt and Seida, 2004).

I also consider a number of factors related to the availability of preannouncement information and prior information disclosure. Firm size, *SIZE*, is the logarithm of market value of equity measured at the fiscal quarter-end preceding day  $t$  and is a proxy for the level of prior information disclosure (Bamber, 1986; Bamber, 1987; Atiase and Bamber, 1994). *LPRIOR\_DISP* is a proxy for the dispersion of investors' beliefs and pre-disclosure information asymmetry prior to the earnings announcement (Atiase and Bamber, 1994; Bamber, Barron and Stober, 1997). Following Bamber, Barron and Stober (1997), I define *LPRIOR\_DISP* the logarithm of  $0.00001 +$  the standard deviation of analysts' forecasts issued within 60 days prior to day  $t - 1$ , scaled by the stock price at the end of the fiscal quarter preceding day  $t$ .<sup>23</sup> *NUM\_EST* is the logarithm of the number of analysts issuing a quarterly earnings forecast within 60 days prior to day  $t - 1$ , and is a proxy for the rate of information flow (Hong, Lim and Stein, 2000).

I include a proxy for the bid-ask spread at the earnings announcement date. The bid-ask spread (trading days) ITD requisite holding period. For example, an investor that purchased shares 100 trading days before the earnings announcement date will have exactly 150 trading days remaining in their ITD requisite holding period (i.e.,  $250 - 100 = 150$ ).

<sup>22</sup>In Section 4.4, I also consider a number of other proxies for the *intensity* component of risk, such as idiosyncratic and systematic return volatilities, as well as the skewness of the daily return distribution.

<sup>23</sup>A small constant of 0.00001 is added to avoid log transforming values that are close to or equal to zero.

represents another important transaction cost to investors that may influence investors' decisions to trade. Atkins and Dyl (1997) provide empirical evidence that annual trading volume is decreasing in the magnitude of the bid-ask spread. Following Atkins and Dyl (1997), I compute the average bid-ask spread,  $BID\_ASK$ , for each observation as follows:

$$BID\_ASK = \frac{1}{10} \sum_{n=2}^{11} \frac{ASK_{j,t-n} - BID_{j,t-n}}{(ASK_{j,t-n} + BID_{j,t-n})/2},$$

where  $BID_{j,t-n}$  and  $ASK_{j,t-n}$  are the closing bid and ask prices for firm  $j$  on day  $t - n$ . Finally, I control for potential differences in stock exchange listings by including an indicator variable,  $NASDAQ$ , that is equal to one if the stock is listed on the NASDAQ exchange and is equal to zero otherwise.

## 4 Empirical Analysis

The purpose of this section is to test the empirical implications of my model analyzed in section 2. Section 4.1 presents univariate statistics for selected regression variables. In section 4.2, I empirically examine the model's necessary condition by testing whether ITDs significantly influence trading decisions around quarterly earnings announcements. Next, I present the fundamental empirical contributions of the paper by decomposing the risk of future adverse price changes into two components: the *duration* and the *intensity* of the risk. In section 4.3, I test whether *duration* (i.e., the length of time that a risk must be borne before an investor meets the ITD holding period requirement) affects trading volume around quarterly the earnings announcements. Finally, in section 4.4, I investigate how the *intensity* of risk interacts with ITD incentives to influence trading volume.

### 4.1 Descriptive Statistics

Table 1 presents the sample distribution of selected regression variables. Abnormal trading volume around quarterly earnings announcements,  $AVOL$ , has a mean and standard deviation of 1.849 and 3.114, respectively, which are comparable to the values reported in Blouin, Raedy and Shackelford (2003). The mean  $\Delta RATE$  is 0.161 and exhibits considerable variation over the sample period. The

mean (median) market value of equity is \$3.019 (\$0.726) billion and the mean (median) number of analysts following each firm is 6.836 (5).

Table 2 presents Pearson and Spearman correlation statistics for selected variables used in multivariate tests. Of particular interest is the Pearson (Spearman) correlation of 0.013 (0.028) between *AVOL* and *ITD*, which is not consistent with investors postponing trades as the ITD cost increases. However, this positive correlation is misleading as it does not control for other factors that influence trading volume. In particular, it fails to account for  $\Delta RATE$  and  $\bar{\Delta}P$ , which represent the main effects associated with *ITD*. In contrast, the Pearson (Spearman) correlation of  $-0.042$  ( $-0.062$ ) between *AVOL* and  $\Delta RATE$  is consistent with investors trading less at the earnings announcement date when the incremental ITD rate is higher.

## 4.2 Testing the Necessary Condition: Do ITDs Influence Trading Volume?

The purpose of this section is to empirically test the necessary condition established in the theoretical framework of Section 2. Recall that the necessary condition states that ITDs must significantly influence investors' trading decisions for risk to affect trading volume. As discussed earlier, Blouin, Raedy and Shackelford (2003) and Hurtt and Seida (2004) document empirical evidence consistent with the necessary condition around quarterly earnings announcement dates, providing preliminary support for the necessary condition and serving as a benchmark for my tests. I test for the necessary condition using my sample and empirical proxy for the ITD incentive to postpone trading and find supporting evidence that compliments the results of prior studies. Testing the necessary condition is intended to provide a foundation, and serve as a point of departure, for examining the main empirical implications of my model: how risk influences investors' trading decisions around quarterly earnings announcements in given ITD incentives to postpone trade.

To test the necessary condition, I employ the following OLS regression model:

$$AVOL = \beta_0 + \beta_1 \Delta RATE + \beta_2 \bar{\Delta}P + \beta_3 ITD + controls + \epsilon, \quad (15)$$

where a negative sign associated with  $\beta_3$  is consistent with the necessary condition. Table 3, Column 1 presents the results from this analysis on the entire sample. Consistent with satisfying the

necessary condition, I find that  $\beta_3$  is negative and statistically significant.<sup>24</sup> This result complements similar evidence documented by Blouin, Raedy and Shackelford (2003) and Hurtt and Seida (2004), and provides preliminary evidence that the necessary condition is satisfied in my sample.

Is this result attributable to ITD effects? Recall that investors are only taxed on realized trading profits (i.e., only if an asset has appreciated in value), but do not receive a direct ITD benefit (in the form of a tax subsidy) from the sale of assets that have depreciated.<sup>25</sup> Therefore, investors' trading decisions when the asset has depreciated in value should be much less sensitive to ITD costs (i.e., the necessary condition may not be satisfied) compared to an asset that has appreciated in value and will generate an ITD tax. The asymmetric nature of tax incentives for appreciated versus depreciated assets provides a discriminating prediction capable of providing additional evidence attributable to an ITD effect. Specifically, I expect *AVOL* to exhibit a negative association with *ITD* when the aggregate price change over the prior holding period is greater than zero. Conversely, I expect to find no such relationship among stocks that have not appreciated over the holding period. Following Blouin, Raedy and Shackelford (2003), I separate the sample into appreciated (i.e.,  $\bar{\Delta}P > 0$ ) and depreciated (i.e.,  $\bar{\Delta}P < 0$ ) observations and estimate equation (15) for each sample. If the results in Column 1 are attributable to ITD incentives to postpone trading, then I expect to find a negative sign on  $\beta_3$  for the appreciated sample and an insignificant  $\beta_3$  coefficient for the depreciated sample. Table 3, Columns 2 and 3 present results for the appreciated and depreciated samples, respectively. Consistent with a tax-related explanation, I find that  $\beta_3$  for the appreciated sample is negative and significant (Column 2), while  $\beta_3$  for the depreciated sample is slightly positive and statistically insignificant (Column 3).<sup>26</sup>

The empirical results of this section provide evidence that investors' trading decisions around quarterly earnings announcements are sensitive to ITD incentives to postpone trade. The results presented in Table 3 provide evidence that that the necessary condition of my model is satisfied and provides a foundation for testing the model's two main empirical implications.

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<sup>24</sup>Standard errors for all specifications account for clustering at the firm level (see Peterson, 2008).

<sup>25</sup>As discussed earlier, investors may receive an indirect ITD benefit if they are able to offset a portion of a realized capital gain in an appreciated asset with a realized capital loss in another asset.

<sup>26</sup>Blouin, Raedy and Shackelford (2003) find similar results using a similar sample partition.

### 4.3 The Impact of the *Duration* of Risk on Trading Volume

This section tests Empirical Implication 1, which states that as *duration* (i.e., the amount of time remaining in the requisite ITD holding period) increases, investors' trading decisions become less sensitive to ITD costs. This occurs because an investor who does not trade now must bear the risk of adverse price changes until the end of the requisite holding period. As this length of time increases (i.e., the longer the investor must bear such risk), the more willing they are to incur the ITD cost by prematurely trading to avoid the higher risk of adverse price changes. I term this effect the "*duration* of risk."

The results of the previous section indicate a need to consider the ITD incentives of all taxable investors. The average ITD measure, used in the prior tests, equally weights each day's price appreciation across all holding periods. Thus, the  $\beta_3$  coefficient in (15) only measures the average ITD incentive among investors and is not capable of discriminating among the different risk-sharing incentives among investors with different amounts of time remaining until qualification.

To empirically test this prediction, I disaggregate the price change,  $\bar{\Delta}P$ , and *ITD* variables in (15) into the 248 individual holding period components and include each as a separate explanatory variable. In other words, instead of one aggregate ITD variable, I now include 248 ITD variables, one for each day in the requisite holding period. This allows me to estimate a separate ITD coefficient for investors with a different *duration* of risk incentives. For example, I include the price change, and corresponding ITD incentive, over the prior 248 days (day  $t - 250$  to  $t - 2$ ) as a separate explanatory variable, which represents an investor that has exactly one day remaining in their ITD requisite holding period. Within the same regression model, I also include the price change and ITD incentive of an investor that purchased shares five days prior to the earnings announcement and has 245 days remaining in their ITD requisite holding period. If investors consider the *duration* of risk when trading, then I expect the ITD incentive of the investor with one day remaining,  $ITD_1$ , to have a more negative coefficient than the ITD incentive of the investor with 245 days left,  $ITD_{245}$ . This follows as investors with a longer amount of time remaining in their ITD holding period are more willing to incur the higher ITD costs by prematurely trading in an effort to avoid having to face adverse price risk over a long duration of time.

To test the *duration* of risk effect, I estimate the following regression model,

$$AVOL = \beta_0 + \sum_{d=1}^{248} \beta_{\Delta P}(d) \cdot \Delta P_d + \sum_{d=1}^{248} \beta_{ITD}(d) \cdot ITD_d + controls + \epsilon, \quad (16)$$

where  $\Delta P_d = \ln(P_{t-2}) - \ln(P_{t-(250-d)}) \equiv \ln(P_{t-2}) - \ln(P_{t-n})$  and  $ITD_d = \Delta RATE \cdot P_d$ . This specification suffers from two problems that prevent a reasonable estimation. First, adding the individual price changes and ITD incentives from the prior year requires the estimation of approximately 500 additional coefficients, which significantly reduces the degrees of freedom. Second, many of the holding period price changes,  $\Delta P_d$ , are estimated across overlapping time periods, which introduces significant multicollinearity problems among the explanatory variables. For example, the price change of an investor with a duration of one day represents a cumulative 247-day price change. Similarly, within the same observation, an investor with a duration of two days has a 246-day price change. Both price changes share 246 daily price changes, which means they will be highly correlated. When severe multicollinearity exists, it becomes very difficult to precisely identify the separate effects among the explanatory variables. As a consequence, coefficient estimates will exhibit large sampling variances (see Judge et al., 1985). This problem is further compounded by the inclusion of the remaining 246 price change variables, as well as 248 highly correlated  $ITD_d$  variables.

To circumvent both of these problems, I employ a MIXed DATA Sampling (MIDAS) regression to estimate (16). MIDAS regression models, recently developed by Ghysels, Santa-Clara and Valkanov (2006) and Ghysels, Sinko and Valkanov (2007), represent a simple, parsimonious, and flexible class of regression models that allows the dependent variable to be sampled at a low frequency (e.g., quarterly earnings announcements) while explanatory variables are sampled at a high frequency (e.g., daily price changes). MIDAS regressions resolve severe multicollinearity problems by restricting the 248 individual coefficient estimates on  $\Delta P_d$  and  $ITD_d$  to be a function of a small-dimensional vector of parameters.<sup>27</sup> Restricting the individual coefficients in this way injects additional information into the regression through the parameterizing function, which imposes a large number of coeffi-

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<sup>27</sup>Restricting the coefficients to a parametric function is similar in spirit to traditional distributed lag models that use data sampled at the same frequency. See Gonedes (1971), Falk and Miller (1977), and Sougiannis (1994) for accounting applications of traditional distributed lag models.

cient constraints.<sup>28</sup> This reduces the sampling variability of coefficient estimates and counteracts increased variability from multicollinearity (see Judge et al., 1985; Kennedy, 2003).

While a number of potential parametric functions exist that are capable of describing the coefficient constraints, I restrict both  $\beta_{\Delta P}(d)$  and  $\beta_{ITD}(d)$  to second-order polynomial functions of *duration*,  $d$ . Specifically, the MIDAS regression estimates (16) subject to the following coefficient restrictions,

$$\begin{aligned}\beta_{\Delta P}(d) &= \alpha_0 + \alpha_1 \cdot d + \alpha_2 \cdot d^2, \\ \beta_{ITD}(d) &= \gamma_0 + \gamma_1 \cdot d + \gamma_2 \cdot d^2,\end{aligned}$$

where  $\alpha_k$  and  $\gamma_k$  are parameters estimated by the MIDAS regression model. The use of a polynomial function to parameterize the coefficient estimates is *ad hoc*. However, a polynomial function has an advantage in that it permits the function to assume opposite signs at different points in the estimation window. For example, the coefficient on  $ITD_d$  for an investor with a duration of one (248) day(s) can have a negative (positive) sign. Conversely, other parametric forms commonly employed in MIDAS regressions, such as an exponential function (Ghysels, Santa-Clara and Valkanov, 2005), restrict the coefficient function to have the same sign across the estimation window.<sup>29</sup> Because I have no *a priori* reason for such a restriction, I select a polynomial function to allow for more flexibility in the parameter estimation. As suggested by Judge et al. (1985), I select a second-order polynomial because it has the lowest Akaike Information Criterion (AIC) among other models with a polynomial restriction of order one (a linear restriction) through six.<sup>30</sup>

While the MIDAS regression mitigates severe multicollinearity problems, it introduces a heteroscedasticity problem among the individual  $\Delta P_d$  regressors. As the first row of Table 4 illustrates, the sample variance of  $\Delta P_d$  is increasing in the holding period (or decreasing in  $d$ ) over which the price change was computed. In OLS regressions, heteroscedasticity between explanatory variables

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<sup>28</sup>Specifically, the number of coefficient constraints is equal to the number of coefficients estimated minus the dimension of the parameter space.

<sup>29</sup>A common application of MIDAS regression models is the estimation of conditional volatility models. Imposing the exponential function upon past return observations guarantees that the coefficient estimates are all positive, which ensures a non-negative estimate of the conditional variance. My results are qualitatively similar when an exponential function is specified in lieu of a second-order polynomial function.

<sup>30</sup>AIC, first proposed by Akaike (1974), is a measure of the goodness-of-fit of an estimated statistical model. It weighs the complexity of an estimated model against how well the model fits the data.

is not a concern because the coefficient estimates adjust for such scale differences. However, in a MIDAS regression, the coefficient estimates are not capable of rescaling the individual differences in variance across the MIDAS regressors because they are constrained to a common parametric function. To alleviate this problem, I scale  $\Delta P_d$ , and thus  $ITD_d$ , by the square root of  $n - 2$  (the number of days the price change was computed over).<sup>31</sup> The second row of Table 4 illustrates that the sample variances of  $\Delta P_d$  scaled by the square root of  $n - 2$  across all holding periods are approximately the same. The final MIDAS regression model is given by,

$$AVOL = \beta_0 + \sum_{d=1}^{248} \beta_{\Delta P}(d) \cdot \frac{\Delta P_d}{\sqrt{n-2}} + \sum_{d=1}^{248} \beta_{ITD}(d) \cdot \frac{ITD_d}{\sqrt{n-2}} + controls + \epsilon, \quad (17)$$

$$\text{subject to } \beta_{\Delta P}(d) = \alpha_0 + \alpha_1 \cdot d + \alpha_2 \cdot d^2, \quad (18)$$

$$\beta_{ITD}(d) = \gamma_0 + \gamma_1 \cdot d + \gamma_2 \cdot d^2. \quad (19)$$

Table 5 presents parameter estimates from (17). Consistent with my empirical predictions, I find that  $\gamma_0$  is negative and statistically significant and  $\gamma_1$  is positive and statistically significant. This implies that the negative relationship between  $AVOL$  and  $ITD_d$  is increasing (or becoming less negative) as the *duration*,  $d$ , of time investors must bear risk increases. Finally,  $\gamma_2$  is negative, but not statistically significant, indicating a small degree of concavity in the coefficient function describing  $\beta_{ITD}(d)$ . Other control variables have similar signs and magnitudes as those reported in Table 3, Column 1.

Figure 1 presents a plot of  $\beta_{ITD}(d)$  as a function of the *duration* of risk,  $d$ , and illustrates how the sensitivity of investors' trading decisions to ITD costs changes with *duration*. Specifically, the sensitivity of investors' trading decisions to ITD costs is increasing (or becoming less negative) in *duration*. This is consistent with the notion that, all else equal, when investors face more uncertainty in the future (i.e., have a longer time to wait), postponing trade becomes more costly from a risk perspective, and thus the ITD incentive to postpone trading becomes relatively less important than the incentive to trade for risk-sharing purposes.

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<sup>31</sup>Scaling the price change by the square root of the number of days in the holding period is motivated by prior evidence that changes in daily stock prices are independently distributed. To the extent this is true, the variance of price changes should be an increasing linear function of time between price measurements.

#### 4.4 The Impact of the *Intensity* of Risk on Trading Volume

This section tests Empirical Implication 2, which states that as the *intensity* of price fluctuations per unit of time increases, investors’ trading decisions become less sensitive to ITD costs. Holding *duration* of risk and the ITD incentive to postpone trading constant, stocks with a higher expected daily return volatility pose more risk of adverse future price changes than do lower volatility stocks. I term this effect the “*intensity* of risk.”

To test this prediction, I run the MIDAS regression specified in (17), but alter the coefficient functions, (18) and (19), as follows:

$$\beta_{\Delta P}(d) = \alpha_0 + \alpha_1 \cdot d + \alpha_2 \cdot d^2 + \alpha_{int} \cdot INTENSITY, \quad (20)$$

$$\beta_{ITD}(d) = \gamma_0 + \gamma_1 \cdot d + \gamma_2 \cdot d^2 + \gamma_{int} \cdot INTENSITY, \quad (21)$$

where a positive  $\gamma_{int}$  is consistent with Empirical Implication 2 and *INTENSITY* is expressed as a sample rank.<sup>32</sup>

Table 6 presents the parameter estimates from (17), subject to (20) and (21). Consistent with my empirical predictions, I find the coefficient  $\gamma_{int}$  is positive and statistically significant at the 10% level (*t*-stat of 1.75), which signifies that the function describing  $\beta_{ITD}(d)$  (as in Figure 1) shifts upward as *INTENSITY* increases. This implies that investors’ trading decisions become less sensitive to ITD costs as postponing trade becomes more costly from a risk-sharing perspective. Therefore, investors are more likely to pay the higher ITD cost to hedge the risk of intense price movements, holding *duration* constant. In addition the coefficients  $\gamma_0$  and  $\gamma_1$  associated with *duration* are similar to the values reported in Table 5. All other control variables exhibit similar values to those reported in previous specifications.

Recall from the analysis in Section 4.2, that investors have asymmetric ITD incentives depending on whether the price has appreciated or depreciated over the prior holding period. The previous MIDAS specifications do not account for such differences in appreciated and depreciated prices and

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<sup>32</sup>My model clearly predicts that trading volume is a function of the variance, and not the standard deviation, of anticipated stock prices. However, this is an artifact of the stylized nature of the model’s assumptions and there is no reason to believe that investors do not consider the standard deviation instead of the variance. In order to avoid any non-linear differences between the two measures, I use sample ranks because both the standard deviation and variance will have exactly the same rank order. All other measures of *INTENSITY* I consider in the section are expressed as a sample rank.

therefore, differences in ITD incentives to postpone trading. A potential solution is to partition the sample based on whether the stock has an average appreciation or an average depreciation over the prior holding period (see Section 4.2 and results in Table 3, Columns 2 and 3). However, even if the average investor holding a stock has an appreciated basis, some investors within the same stock will have a depreciated basis (as purchase prices vary over the prior holding period) and therefore, different ITD incentives than an investor with an appreciated basis. Classifying observations based on the average amount of price appreciation will destroy the information regarding asymmetric ITD costs across different holding periods within the same observation. To circumvent this problem, I exploit the flexible nature of MIDAS regression models by allowing appreciated holding periods to have different polynomial functions describing  $\beta_{\Delta P}(d)$  and  $\beta_{ITD}(d)$  than depreciated holding periods. Specifically, (20) and (21) are adjusted as follows:

$$\begin{aligned} \beta_{\Delta P}(\theta) = & APP_d \cdot (\alpha_0^A + \alpha_1^A \cdot d + \alpha_2^A \cdot d^2 + \alpha_{int}^A \cdot INTENSITY) \\ & + DEP_d \cdot (\alpha_0^D + \alpha_1^D \cdot d + \alpha_2^D \cdot d^2 + \alpha_{int}^D \cdot INTENSITY), \end{aligned} \quad (22)$$

$$\begin{aligned} \beta_{ITD}(\theta) = & APP_d \cdot (\gamma_0^A + \gamma_1^A \cdot d + \gamma_2^A \cdot d^2 + \gamma_{int}^A \cdot INTENSITY) \\ & + DEP_d \cdot (\gamma_0^D + \gamma_1^D \cdot d + \gamma_2^D \cdot d^2 + \gamma_{int}^D \cdot INTENSITY), \end{aligned} \quad (23)$$

where  $\theta \in \{d, INTENSITY, APP_d, DEP_d\}$ ,  $APP_d$  is an indicator variable equal to one if the change in stock price for an investor with duration,  $d$ , is positive (i.e.  $\Delta P_d > 0$ ), equal to zero otherwise, and  $DEP_d$  is an indicator variable equal to one if the change in stock price for an investor with duration,  $d$ , is not positive (i.e.  $\Delta P_d \leq 0$ ) and equal to zero otherwise. If investors have asymmetric ITD incentives with respect to appreciated and depreciated holding periods, then I expect the previous MIDAS results for  $\beta_{ITD}(\theta)$  to reflect the influence of appreciated days (i.e.,  $\gamma_\theta^A$  coefficients are statistically significant with the correct sign) rather than the influence of depreciated days (i.e.,  $\gamma_\theta^D$  coefficients are not statistically significant).

Table 7 presents the parameter estimates associated with  $\beta_{ITD}(\theta)$  from (17), subject to (22) and (23). Consistent with an asymmetric ITD incentive between appreciated and depreciated price changes, I find the coefficient estimates associated with appreciated holding periods (i.e.,  $\gamma_\theta^A$ ) have the predicted sign and are statistically significant. In particular the coefficient  $\gamma_{int}^A$  is now statistically significant at the 1% level ( $t$ -stat of 2.69) with a magnitude similar the value reported

in Table 6. In contrast, the estimates associated with depreciated holding periods (i.e.,  $\gamma_{\theta}^D$ ) do not consistently have the predicted sign and are all statistically insignificant at the 10% level.

In addition to variance of the daily stock return distribution, I also consider three other proxies for the *intensity* component of risk: (1) the idiosyncratic variance of daily returns, (2) the systematic (market and 2-digit industry) variance of daily returns, and (3) the coefficient of skewness of the daily return distribution. First, I examine whether the *INTENSITY* results in Tables 6 and 7 are driven by idiosyncratic risk, systematic risk, or both, by decomposing the total return variance, *INTENSITY*, into the idiosyncratic variance, *IDIO*, and the systematic variance, *SYST*. Specifically, *IDIO* and *SYST* are equal to the variance of the residual and predicted values (expressed as a sample rank), respectively, from a regression of firm-specific returns on the CRSP value-weighted market return and the 2-digit industry return (for example, see Roll, 1988), estimated over the 100 trading days immediately preceding day  $t - 1$ , where  $t$  is the quarterly earnings announcement date. Results for this specification are presented in Table 8, Column 1. I find  $\gamma_{idio}^A$  is positive and statistically significant, while  $\gamma_{syst}^A$  is slightly negative and statistically insignificant. These results indicate that if investors attempt to hedge their risks (e.g., by short selling similar assets), it may be difficult to find a substitute asset to hedge the idiosyncratic risk of adverse price changes while waiting to ITD holding period to expire. Conversely, systematic risk does not significantly influence the sensitivity of investors' trading decisions to ITD costs.

Second, I examine the degree to which a firm's stock is "crash prone" by examining the degree of left-skewness in the daily return distribution. Specifically, I define *SKEW* as the negative coefficient of skewness (expressed as a sample rank) of the firm-specific daily price change distribution, estimated over the 100 trading days immediately preceding day  $t - 1$ . Following Chen, Hong and Stein (2001), I compute *SKEW* as follows:

$$SKEW = -\frac{100 \cdot 99^{3/2} \cdot \sum_{n=2}^{101} R_{t-n}^3}{99 \cdot 98 \cdot \left(\sum_{n=2}^{101} R_{t-n}^2\right)^{3/2}},$$

where  $R_{t-n}$  is the logarithm of the daily change in stock price on day  $t - n$ . Placing a minus sign on the coefficient of skewness adopts the convention that a higher value of *SKEW* corresponds to a higher risk of a stock price "crash." Table 8, Column 2 presents results for the MIDAS specification in which *INTENSITY* is replaced with *SKEW*. Consistent with the *INTENSITY* results from Table

7, I find that  $\gamma_{skew}^A$  is positive indicating that investors trading decisions become less sensitive to ITD costs as the probability of large stock price “crash” (i.e. high *SKEW*) increases. However, this coefficient is not statistically significant (*t*-statistic of 1.52).

Finally, prior research documents a positive correlation between stock price volatility and the degree of institutional ownership in a firm (e.g., Potter, 1992; Sias, 1996). Many institutions are exempt from paying capital gains taxes leaving them with no ITD incentive to postpone trading. Because *INTENSITY* is based on the stock price volatility, it may simply serve as a proxy for the degree of institutional ownership and, therefore, capturing the average tax status among traders at the quarterly earnings announcement date, rather than the risk of adverse price changes that investors’ subject to an ITD consider. I examine this possibility by computing the fraction of a firm’s stock owned by institutional investors to see if it eliminates the statistical significance or changes the sign of  $\gamma_{idio}^A$  in Table 8, Column 1. Specifically, I include the percentage of shares held by 13-f filing institutions, *INST* (expressed as a sample rank), computed at the end of the calendar quarter immediately preceding the earnings announcement date. The results in Table 8, Column 3 show that  $\gamma_{idio}^A$  remains negative and statistically significant, while  $\gamma_{inst}^A$  is positive and statistically insignificant. The lack of significance associated with  $\gamma_{inst}^A$  is consistent with the empirical evidence in Blouin, Raedy and Shackelford (2003) illustrating that the degree of institutional ownership does not provide a discriminating ITD result for their sample. This indicates that *INST* may be a poor proxy for the true (unobservable) tax-status of cross-section of traders around the earnings announcement. Consequently, I cannot rule out the possibility that *INTENSITY* is simply a proxy for the fraction of investors that are subject to an ITD cost.

## 5 Conclusions

This paper theoretically and empirically investigates how the risk of future adverse price changes created by the anticipated arrival of information influences risk-averse investors’ trading decisions in institutionally imperfect capital markets. I examine the relationship between trading volume and the risk of adverse price changes, as measured by stock price volatility, in the presence of trading frictions created by the existence of intertemporal tax discontinuities (ITDs). An ITD refers to the incremental capital gains tax rate applied to trading profits on shares held for less than a requisite

amount of time. Specifically, I examine how trading volume is influenced by the trade-off between the risk-sharing benefits of immediate trade to mitigate exposure to future adverse price changes, and explicit transaction costs imposed upon such trades by the existence of an ITD.

Employing a stylized model, I demonstrate that current trading decisions depend upon two aspects of risk: the expected intensity of future price fluctuations per unit of time and the duration of time that risk must be borne. Tension in the model is created by introducing an incremental capital gains tax rate applied to trading profits on shares held for less than a requisite amount of time. Thus, risk-averse investors face an economic tension between trading immediately to an optimal risk-sharing portfolio at the cost of incurring an incremental tax on realized trading profits, versus postponing trade to avoid the incremental tax while facing the risk of interim, adverse price changes. Specifically, I find that the total amount of risk that each investor considers is an increasing function of both the *intensity* and the *duration* of the risk of adverse price changes. Intuitively, intensity captures the risk of adverse price movements per unit of time, while duration captures the amount of time that such risk must be held. The fact that investors can reduce tax costs by postponing the sale of shares until a known future point in time creates a unique opportunity to empirically investigate the impact of the duration of risk on trading behavior.

I empirically examine whether the duration of risk affects trading volume around quarterly earnings announcements by employing a MIDAS regression framework. Consistent with the model's predictions, I document evidence that as the number of days left to avoid the incremental tax increases (i.e., duration of risk increases), trading volume around quarterly earnings announcements is less sensitive to the incremental tax on short-term trading profits. Similarly, as the expected volatility of future stock price increases (i.e., intensity increases), trading volume is less sensitive to incremental tax costs. These results suggest that investors are more willing to incur explicit tax costs in order to insulate themselves against increases in the risk of price fluctuations driven by increases in the duration or intensity of risk. Overall, my analysis provides a novel and powerful setting in which to directly examine empirical implications of the adverse risk-sharing effect of anticipated information.

## A Appendix

### A.1 Derivation of Lemma 1

Consider the period 1 problem of an investor of type  $i$ , subject to a tax rate  $\tau_i$ :

$$\underset{D_{1,i}}{\text{Max}} E_{\tilde{u}, \tilde{P}_2} \left[ -\exp \left( -\tilde{W}_i / \gamma \right) \right],$$

$$\begin{aligned} \text{where } \tilde{W}_i = & E_i + P_{0,i} D_{0,i} + (P_1 - P_{0,i})(D_{0,i} - D_{1,i}) + (\tilde{P}_2 - P_{0,i})(D_{1,i} - D_{2,i}) \\ & + (\tilde{u} - P_{0,i}) D_{2,i} - \tau_i (P_1 - P_{0,i})(D_{0,i} - D_{1,i}). \end{aligned}$$

Substituting the relation  $D_{2,i} = x$  (from equation 4) and omitting terms unrelated to  $D_{1,i}$ ,  $\tilde{P}_2$ , or  $\tilde{u}$ , the objective function simplifies to:

$$E_{\tilde{u}, \tilde{P}_2} \left[ -\exp \left\{ -\frac{1}{\gamma} \left[ \tilde{P}_2 - P_1 (1 - \tau_i) - P_{0,i} \tau_i \right] D_{1,i} - \frac{1}{\gamma} (\tilde{u} - \tilde{P}_{2,i}) x \right\} \right].$$

Using the moment-generating function of the normal random variable,  $\tilde{P}_2$ , and dropping the term  $(1/\gamma)(\tilde{u} - \tilde{P}_{2,i})x$  because it is unrelated to the choice variable,  $D_{1,i}$ , investor  $i$ 's problem becomes:

$$\underset{D_{1,i}}{\text{Max}} -\exp \left\{ -\frac{1}{\gamma} \left[ E[\tilde{P}_2] - P_1 (1 - \tau_i) - P_{0,i} \tau_i \right] D_{1,i} + \frac{1}{\gamma^2} D_{1,i}^2 \text{Var}[\tilde{P}_2] \right\}.$$

Differentiating this expression with respect to  $D_{1,i}$ , setting it equal to zero, and solving for  $D_{1,i}$  yields:

$$D_{1,i} = \frac{\left[ E[\tilde{P}_2] - P_1 (1 - \tau_i) - P_{0,i} \tau_i \right]}{\frac{1}{\gamma} \text{Var}[\tilde{P}_2]}.$$

At this point, there are two potential equilibria in period 1: (1) *Sellers* dispose of shares and *Buyers* acquire shares (i.e., all investors trade toward optimal risk-sharing) and (2) *Sellers* acquire shares and *Buyers* dispose of shares (i.e., all investors trade away from optimal risk-sharing).

Consider the first potential equilibrium. If *Sellers* sell shares in period 1, then they will incur a tax,  $\tau_{S_1} = \tau_{S_2} = \tau$ , on any trading profits. Conversely, *Buyers* will not pay taxes,  $\tau_B = 0$ , on any

shares they purchase in period 1. Consequently, the demand functions of *Buyers*, *Sellers<sub>1</sub>*, and *Sellers<sub>2</sub>* can be expressed, respectively, as

$$D_{1,B} = \frac{[E[\tilde{P}_2] - P_1]}{\frac{1}{\gamma} \text{Var}[\tilde{P}_2]}, \quad (\text{A1})$$

$$D_{1,S_1} = \frac{[E[\tilde{P}_2] - P_1(1 - \tau) - P_{0,S_1}\tau]}{\frac{1}{\gamma} \text{Var}[\tilde{P}_2]}, \quad (\text{A2})$$

$$D_{1,S_2} = \frac{[E[\tilde{P}_2] - P_1(1 - \tau) - P_{0,S_2}\tau]}{\frac{1}{\gamma} \text{Var}[\tilde{P}_2]}. \quad (\text{A3})$$

Applying the market clearing condition and substituting (A1)–(A3):

$$\begin{aligned} x &= \int D_{1,i} di \\ &= \theta [\delta \cdot D_{1,S_1} + (1 - \delta) \cdot D_{1,S_2}] + (1 - \theta) D_{1,B} \\ &= \frac{E[\tilde{P}_2] - P_1 [(1 - \tau)\theta + (1 - \theta)] - \theta\tau [\delta P_{0,S_1} + (1 - \delta)P_{0,S_2}]}{\frac{1}{\gamma} \text{Var}[\tilde{P}_2]} \\ &= \frac{E[\tilde{P}_2] - P_1(1 - \theta\tau) - \theta\tau\bar{P}_0}{\frac{1}{\gamma} \text{Var}[\tilde{P}_2]} \end{aligned}$$

where  $\bar{P}_0 = \delta P_{0,S_1} + (1 - \delta) P_{0,S_2}$ . The unconditional expectation and variance of  $\tilde{P}_2$ , from (3) is given by:

$$E[\tilde{P}_2] = \bar{u} - \frac{x}{\gamma(h + Ns)}, \quad (\text{A4})$$

$$\text{Var}[\tilde{P}_2] = \frac{Ns}{h(h + Ns)}. \quad (\text{A5})$$

Substituting (A4) and (A5) into the market clearing condition and solving for  $P_1$  yields:

$$\begin{aligned} P_1 &= \frac{E[\tilde{P}_2] - \frac{x}{\gamma} \text{Var}[\tilde{P}_2] - \theta\tau\bar{P}_0}{1 - \theta\tau} \\ &= \frac{\bar{u} - \frac{x}{\gamma(h + Ns)} - \frac{xNs}{\gamma h(h + Ns)} - \theta\tau\bar{P}_0}{1 - \theta\tau} \\ &= \frac{\bar{u} - \frac{x}{\gamma h} - \theta\tau\bar{P}_0}{1 - \theta\tau}, \quad (\text{A6}) \end{aligned}$$

which is identical to (5). Substituting (A4), (A5), and (A6) into (A1)–(A3) and simplifying each expression gives:

$$D_{1,S_1} = x + \frac{\gamma h \left(1 + \frac{h}{N_s}\right) \tau (1 - \theta) \left[\bar{u} - \frac{x}{\gamma h} - \frac{(1-\theta\tau)}{(1-\theta)} P_{0,S_1} - \tau \bar{P}_0\right]}{(1 - \theta\tau)} \quad (\text{A7})$$

$$D_{1,S_2} = x + \frac{\gamma h \left(1 + \frac{h}{N_s}\right) \tau (1 - \theta) \left[\bar{u} - \frac{x}{\gamma h} - \frac{(1-\theta\tau)}{(1-\theta)} P_{0,S_2} - \tau \bar{P}_0\right]}{(1 - \theta\tau)} \quad (\text{A8})$$

$$D_{1,B} = x - \frac{\gamma h \left(1 + \frac{h}{N_s}\right) \theta \tau \left[\bar{u} - \frac{x}{\gamma h} - \bar{P}_0\right]}{(1 - \theta\tau)} \quad (\text{A9})$$

which are identical to (6), (7), and (8), respectively.

Note that *Buyers* demand function, given by (A9), can be rewritten as follows:

$$\begin{aligned} D_{1,B} &= x - \frac{\gamma h \left(1 + \frac{h}{N_s}\right) \theta \tau \left[\bar{u} - \frac{x}{\gamma h} - \bar{P}_0\right]}{(1 - \theta\tau)} \\ &= x - \frac{\theta \tau (P_1 - \bar{P}_0)}{\frac{1}{\gamma} \text{Var}[\bar{P}_2]}. \end{aligned} \quad (\text{A10})$$

Recall that a “good news” announcement assumes  $P_1 > P_{0,i}, \forall i$ , which means that  $P_1$  must be greater than the average  $P_{0,i}$  (i.e.,  $P_1 > \bar{P}_0$ ). It directly follows from (A10) that *Buyers* demand,  $D_{1,B}$ , must be less than the optimal risk-sharing allocation,  $x$ . Therefore, if *Buyers* purchase shares, they buy less than an optimal risk-sharing amount. Similar manipulations of (A7) and (A8) lead to the result that *Sellers* period 1 demand is always greater than the optimal risk-sharing amount,  $x$ .

Next, consider the second potential equilibrium where *Sellers* acquire shares and *Buyers* dispose of shares (i.e., all investors trade away from optimal risk-sharing). If *Sellers* buy shares in period 1, then they do not incur a tax,  $\tau_{S_1} = \tau_{S_2} = 0$ , on any trading profits. Conversely, *Buyers* do pay taxes,  $\tau_B = \tau$ , on the sale of shares in period 1. In this scenario, *Buyers* and *Sellers* swap their tax status and, therefore, swap their demand functions. Therefore, *Buyers* take on the demand function of *Sellers* derived in the first equilibrium, which implies that they desire to hold an amount greater than the optimal risk-sharing amount,  $x$ . Given that *Buyers*, by definition, initially hold an “underweighted” amount,  $D_{0,B} < x$ , the only way they can trade to an amount greater than  $x$  is to purchase additional shares. This is inconsistent with the initial conjecture that *Buyers* sell

shares and demonstrates that the second equilibrium does not exist. Therefore, the unique period 1 equilibrium is one in which *Buyers* (*Sellers*) always buy (sell) shares of the risky asset (i.e.,  $D_{1,B} \geq D_{0,B}$ ,  $D_{1,S_1} \leq D_{0,S_1}$ , and  $D_{1,S_2} \leq D_{0,S_2}$ ). ■

## A.2 Derivation of Proposition 1

Substituting (A10) into (10) and simplifying the expression gives:

$$\begin{aligned}
V_1 &= (1 - \theta)(D_{1,B} - D_{0,B}) \\
&= (1 - \theta) \left( x - D_{0,B} - \frac{\theta\tau(P_1 - \bar{P}_0)}{\frac{1}{\gamma}Var[\tilde{P}_2]} \right) \\
&= V^* - (1 - \theta) \frac{\theta\tau\bar{\Delta}P_1}{\frac{1}{\gamma}Var[\tilde{P}_2]}
\end{aligned}$$

where  $V^* = (1 - \theta)(x - D_{0,B})$ ,  $Var[\tilde{P}_2] = \frac{N_s}{h(h+N_s)}$ , and  $\bar{\Delta}P_1 = P_1 - \delta P_{0,S_1} - (1 - \delta)P_{0,S_2}$ . ■

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**Table 2**  
**Correlation Matrix**

Variable	<i>AVOL</i>	$\Delta RATE$	$\bar{\Delta}P$	<i>ITD</i>	<i>INTENSITY</i>	<i>AUE</i>	<i>SIZE</i>
<i>AVOL</i>		-0.042 *	0.118 *	0.013 *	0.089 *	0.050 *	-0.120 *
$\Delta RATE$	-0.062 *		-0.007	0.021 *	0.021 *	-0.018	0.192 *
$\bar{\Delta}P$	0.116 *	0.034 *		0.079 *	-0.186 *	-0.181 *	0.156 *
<i>ITD</i>	0.028 *	0.109 *	0.199 *		-0.028 *	0.022 *	0.010 *
<i>INTENSITY</i>	0.129 *	-0.021 *	-0.110 *	-0.027 *		0.142 *	-0.238 *
<i>AUE</i>	0.064 *	-0.061	-0.163 *	-0.007 *	0.146 *		-0.229 *
<i>SIZE</i>	-0.120 *	0.143 *	0.155 *	0.028 *	-0.317 *	-0.237 *	

Pearson (Spearman) correlations are presented above (below) the diagonal. The sample includes 67,493 observations of quarterly earnings announcements from 1982 to 2005. Let  $t$  denote the quarterly earnings announcement date identified by Compustat. *AVOL* is 100 times the actual less expected trading volume on days  $t - 1$  to  $t + 1$ , where actual trading volume is the natural logarithm of  $1 +$  the dollar volume on days  $t - 1$  to  $t + 1$ , divided by the logarithm of  $1 +$  the market value of shares outstanding on days  $t - 1$  to  $t + 1$ , and expected trading volume uses a similar ratio for the total market volume adjusted with coefficients from a regression of the firm's actual trading volume on the total market volume for the 100 trading days (after excluding three-day windows around prior quarterly announcements) immediately preceding day  $t - 1$ .  $\Delta RATE$  is the maximum statutory short-term capital gains tax rate minus the maximum statutory long-term capital gains tax rate on day  $t$ .  $\bar{\Delta}P$  is the volume-weighted, average price change over the prior 248 trading days immediately preceding day  $t - 2$  (within the requisite ITD holding period),  $(1/248) \sum_{n=3}^{250} (dVOL_{t-n} / \sum_{m=3}^{500} dVOL_{t-m}) \Delta P_{t-n}$ , where  $\Delta P_{t-n}$  is equal to the logarithm of the stock price on day  $t - 2$  (adjusted for stock splits and stock dividends) minus the logarithm of the stock price on day  $t - n$ ,  $dVOL_{t-n}$  is the daily trading volume on day  $t - n$ , and  $\sum_{m=3}^{500} dVOL_{t-m}$  is the total trading volume over the two years immediately preceding day  $t - 2$ . *INTENSITY* is 100 times the variance of daily changes in the logarithm of stock price estimated over the 100 trading days immediately preceding day  $t - 1$ . *AUE* is the 100 times absolute value of the difference between announced quarterly earnings on day  $t$  and the median analyst forecast within the 60 days preceding day  $t - 1$ , scaled by the share price at the end of the fiscal quarter for which earnings are released. *SIZE* is the logarithm of the market value of equity at the end of the fiscal quarter preceding day  $t$ . \* indicates significance at the 5% level based on two-tailed test.

**Table 3**  
**OLS Determinants of Trading Volume**  
**Around Quarterly Earnings Announcements**

		Dependent Variable: <i>AVOL</i>					
Variable	Pred.	Full Sample		Appreciated ( $\Delta P > 0$ )		Depreciated ( $\Delta P \leq 0$ )	
		Coeff.	( <i>t</i> -stat)	Coeff.	( <i>t</i> -stat)	Coeff.	( <i>t</i> -stat)
<i>INTERCEPT</i>		2.950	(16.49)	3.114	(12.43)	1.816	(7.34)
$\Delta RATE$		-1.083	(-3.05)	-0.668	(-2.12)	0.250	(1.03)
$\bar{\Delta} P^a$		3.115	(8.22)	5.692	(8.49)	1.257	(3.01)
<i>ITD</i> <sup>a</sup>	(-)	<b>-3.723</b>	<b>(-4.05)</b>	<b>-9.624</b>	<b>(-5.01)</b>	<b>0.957</b>	<b>(0.23)</b>
<i>AUE</i> <sup>b</sup>		0.610	(11.47)	0.772	(10.51)	0.419	(5.64)
<i>NONLINEAR</i> <sup>b</sup>		-0.375	(-2.01)	-0.338	(-6.73)	-0.307	(-1.27)
<i>BID_ASK</i> <sup>a</sup>		-0.138	(-6.25)	-0.093	(-3.06)	-0.153	(-3.28)
<i>SIZE</i>		-0.362	(-15.87)	-0.422	(-14.95)	-0.226	(-9.17)
<i>LPRIOR_DISP</i> <sup>a</sup>		0.089	(6.44)	0.053	(3.17)	0.159	(4.20)
<i>NUM_EST</i>		0.413	(9.87)	0.403	(6.38)	0.412	(8.76)
<i>NASDAQ</i>		0.358	(8.33)	0.371	(4.38)	0.218	(3.53)
Adj. R <sup>2</sup>		0.067		0.086		0.021	
Num. Obs.		67,493		40,901		26,592	

<sup>a</sup> Variable winsorized at the 1% and 99% levels.; <sup>b</sup> Variable winsorized at the 99% level.

Let  $t$  denote the quarterly earnings announcement date identified by Compustat. The dependent variable is the three-day abnormal trading volume,  $AVOL$ , around quarterly earnings announcements from 1982 to 2005. Specifically,  $AVOL$  is 100 times the actual less expected trading volume on days  $t - 1$  to  $t + 1$ , where actual trading volume is the natural logarithm of 1 + the dollar volume on days  $t - 1$  to  $t + 1$ , divided by the logarithm of 1 + the market value of shares outstanding on days  $t - 1$  to  $t + 1$ , and expected trading volume uses a similar ratio for the total market volume adjusted with coefficients from a regression of the firm's actual trading volume on the total market volume for the 100 trading days (after excluding three-day windows around prior quarterly announcements) immediately preceding day  $t - 1$ .  $\Delta RATE$  is the maximum statutory short-term capital gains tax rate minus the maximum statutory long-term capital gains tax rate on day  $t$ .  $\bar{\Delta} P$  is the volume-weighted, average price change over the prior 248 trading days immediately preceding day  $t - 2$  (within the requisite  $ITD$  holding period),  $(1/248) \sum_{n=3}^{250} (dVOL_{t-n} / \sum_{m=3}^{500} dVOL_{t-m}) \Delta P_{t-n}$ , where  $\Delta P_{t-n}$  is equal to the logarithm of the stock price on day  $t - 2$  (adjusted for stock splits and stock dividends) minus the logarithm of the stock price on day  $t - n$ ,  $dVOL_{t-n}$  is the daily trading volume on day  $t - n$ , and  $\sum_{m=3}^{500} dVOL_{t-m}$  is the total trading volume over the two years immediately preceding day  $t - 2$ .  $ITD$  is equal to the product of  $\Delta RATE$  and  $\bar{\Delta} P$ .  $AUE$  is the 100 times absolute value of the difference between announced quarterly earnings on day  $t$  and the median analyst forecast within the 60 days preceding day  $t - 1$ , scaled by the share price at the end of the fiscal quarter for which earnings are released.  $NONLINEAR$  is equal to the square of  $AUE$ .  $BID_ASK$  is 100 times the average percentage bid-ask spread over the 10 trading days immediately preceding day  $t - 1$ .  $SIZE$  is the logarithm of the market value of equity at the end of the fiscal quarter preceding day  $t$ .  $LPRIOR_DISP$  is the logarithm of 0.0001 + the standard deviation of analysts' forecasts issued within 60 days prior to day  $t - 1$ , scaled by the stock price at the end of the fiscal quarter preceding day  $t$ .  $NUM_EST$  is the logarithm of the number of analysts issuing a quarterly earnings forecast within 60 days prior to day  $t - 1$ .  $NASDAQ$  is an indicator variable equal to one if the stock is listed on the NASDAQ exchange on day  $t$  and equal to zero otherwise. Coefficient  $t$ -statistics are based on standard errors adjusted for clustering at the firm level.

**Table 4**  
**Variance of Price Change Across Different Holding Periods**

Variable	Number of Days in Holding Period, ( $n - 2$ )						
	1	50	100	125	150	200	250
Var $[\Delta P_d]$	0.091	3.962	8.171	10.134	12.065	16.338	20.224
Var $\left[ \frac{\Delta P_d}{\sqrt{n-2}} \right]$	0.091	0.083	0.083	0.082	0.082	0.083	0.082

This table describes the sample variance of scaled and unscaled price changes across different holding periods,  $n - 2$ , prior to the quarterly earnings announcement date,  $t$ . Let  $n$  denote the number of days prior to the quarterly earnings announcement date that an investor, with  $d$  days remaining from  $t$  in the requisite ITD holding period of 250 trading days, purchased shares.  $\Delta P_d$  is price change over  $n$  trading days immediately preceding day  $t - 2$  and is equal to the logarithm of the stock price on day  $t - 2$  (adjusted for stock splits and stock dividends) minus the logarithm of the stock price on day  $t - n$ . The sample includes 67,493 observations of quarterly earnings announcements from 1982 to 2005.

**Table 5**  
**MIDAS Regression Examining the Duration of Risk and**  
**Trading Volume Around Quarterly Earnings Announcements**

Dependent Variable: <i>AVOL</i>							
MIDAS Parameters	Pred.	Coeff.	( <i>t</i> -stat)	Other Parameters	Coeff.	( <i>t</i> -stat)	
<i>ITD<sub>d</sub></i>	$\gamma_0 \times 10^{-2}$	(-)	-1.102	(-3.29)	<i>INTERCEPT</i>	3.013	(16.42)
	$\gamma_1$	(+)	0.865	(2.73)	<i>ΔRATE</i>	-0.997	(-2.97)
	$\gamma_2 \times 10^3$		-1.610	(-0.12)	<i>AUE<sup>b</sup></i>	0.629	(11.49)
<i>ΔP<sub>d</sub></i>	$\alpha_0 \times 10^{-2}$		1.365	(8.77)	<i>NONLINEAR<sup>b</sup></i>	-0.376	(-2.03)
	$\alpha_1$		1.064	(1.79)	<i>BID_ASK<sup>a</sup></i>	-0.143	(-6.19)
	$\alpha_2 \times 10^3$		2.953	(2.65)	<i>SIZE</i>	-0.389	(-15.24)
					<i>LPRIOR_DISP<sup>a</sup></i>	0.093	(6.23)
					<i>NUM_EST</i>	0.417	(9.69)
				<i>NASDAQ</i>	0.318	(7.94)	

Adj. R<sup>2</sup> = 0.068

<sup>a</sup> Variable winsorized at the 1% and 99% levels.; <sup>b</sup> Variable winsorized at the 99% level.

This table presents parameter estimates from the following MIXed DATA Sampling (MIDAS) regression model:

$$AVOL = \beta_0 + \sum_{d=1}^{248} \beta_{\Delta P}(d) \cdot \Delta P_d + \sum_{d=1}^{248} \beta_{ITD}(d) \cdot ITD_d + controls + \epsilon,$$

$$\begin{aligned} \text{subject to: } \beta_{\Delta P}(d) &= \alpha_0 + \alpha_1 \cdot d + \alpha_2 \cdot d^2, \\ \beta_{ITD}(d) &= \gamma_0 + \gamma_1 \cdot d + \gamma_2 \cdot d^2, \end{aligned}$$

Let  $t$  denote the quarterly earnings announcement date identified by Compustat. The dependent variable is the three-day abnormal trading volume,  $AVOL$ , around 67,493 quarterly earnings announcements from 1982 to 2005. Specifically,  $AVOL$  is 100 times the actual less expected trading volume on days  $t-1$  to  $t+1$ , where actual trading volume is the natural logarithm of 1+the dollar volume on days  $t-1$  to  $t+1$ , divided by the logarithm of 1+the market value of shares outstanding on days  $t-1$  to  $t+1$ , and expected trading volume uses a similar ratio for the total market volume adjusted with coefficients from a regression of the firm's actual trading volume on the total market volume for the 100 trading days (after excluding three-day windows around prior quarterly announcements) immediately preceding day  $t-1$ .  $\Delta P_d$  is the volume-weighted price change over  $n$  trading days immediately preceding day  $t-2$ ,  $(1/248)(dVOL_{t-n}/\sum_{m=3}^{500} dVOL_{t-m})\Delta P_{t-n}/\sqrt{n-2}$ , where  $\Delta P_{t-n}$  is equal to the logarithm of the stock price on day  $t-2$  (adjusted for stock splits and stock dividends) minus the logarithm of the stock price on day  $t-n$ ,  $dVOL_{t-n}$  is the daily trading volume on day  $t-n$ ,  $\sum_{m=3}^{500} dVOL_{t-m}$  is the total trading volume over the two years immediately preceding day  $t-2$ , and  $\sqrt{n-2}$  is a scaling factor to minimize heteroscedasticity in price changes computed across different holding periods.  $ITD_d$  is equal to the product of  $\Delta RATE$  and  $\Delta P_d$ , where  $\Delta RATE$  is the maximum statutory short-term capital gains tax rate minus the maximum statutory long-term capital gains tax rate on day  $t$ . Duration,  $d$ , is the number of trading days from the quarterly earnings announcement date,  $t$ , that an investor, which purchased shares on day  $t-n$ , must hold the stock to meet the requisite ITD holding period of 250 trading days. Other *controls* (defined in Section 3.2) include *AUE*, *NONLINEAR*, *SIZE*, *LPRIOR\_DISP*, *NUM\_EST*, and *NASDAQ*. Coefficient  $t$ -statistics are based on standard errors adjusted for clustering at the firm level.

**Table 6**  
**MIDAS Regression Examining the Intensity of Risk and**  
**Trading Volume Around Quarterly Earnings Announcements**

Dependent Variable: <i>AVOL</i>							
MIDAS Parameters	Pred.	Coeff.	( <i>t</i> -stat)	Other Parameters	Coeff.	( <i>t</i> -stat)	
<i>ITD<sub>d</sub></i>	$\gamma_0 \times 10^{-2}$	(-)	-1.402	(-3.37)	<i>INTERCEPT</i>	2.819	(15.84)
	$\gamma_1$	(+)	0.974	(2.46)	<i>ΔRATE</i>	-2.654	(-4.39)
	$\gamma_2 \times 10^3$		-2.010	(-0.26)	<i>AUE<sup>b</sup></i>	0.581	(11.02)
	$\gamma_{int} \times 10^4$	(+)	2.919	(1.75)	<i>NONLINEAR<sup>b</sup></i>	-0.341	(-3.49)
					<i>BID_ASK<sup>a</sup></i>	-0.208	(-6.98)
$\Delta P_d$	$\alpha_0 \times 10^{-2}$		2.495	(6.95)	<i>SIZE</i>	-0.214	(-9.76)
	$\alpha_1$		0.945	(0.98)	<i>LPRIOR_DISP<sup>a</sup></i>	0.097	(7.09)
	$\alpha_2 \times 10^3$		1.654	(3.45)	<i>NUM_EST</i>	0.347	(6.72)
	$\alpha_{int} \times 10^4$		-1.155	(-7.38)	<i>NASDAQ</i>	0.155	(4.15)
					<i>INTENSITY</i> $\times 10^5$	1.717	(11.02)
Adj. $R^2 = 0.076$							

<sup>a</sup> Variable winsorized at the 1% and 99% levels.; <sup>b</sup> Variable winsorized at the 99% level.

This table presents parameter estimates from the following MIXed DATA Sampling (MIDAS) regression:

$$AVOL = \beta_0 + \sum_{d=1}^{248} \beta_{\Delta P}(\theta) \cdot \Delta P_d + \sum_{d=1}^{248} \beta_{ITD}(\theta) \cdot ITD_d + controls + \epsilon,$$

$$\begin{aligned} \text{subject to: } \beta_{\Delta P}(\theta) &= \alpha_0 + \alpha_1 \cdot d + \alpha_2 \cdot d^2 + \alpha_{int} \cdot INTENSITY, \\ \beta_{ITD}(\theta) &= \gamma_0 + \gamma_1 \cdot d + \gamma_2 \cdot d^2 + \gamma_{int} \cdot INTENSITY, \end{aligned}$$

where  $\theta \in \{d, INTENSITY\}$ . Let  $t$  denote the quarterly earnings announcement date identified by Compustat. The dependent variable is the three-day abnormal trading volume,  $AVOL$ , around 67,493 quarterly earnings announcements from 1982 to 2005. Specifically,  $AVOL$  is 100 times the actual less expected trading volume on days  $t - 1$  to  $t + 1$ , where actual trading volume is the natural logarithm of  $1 +$  the dollar volume on days  $t - 1$  to  $t + 1$ , divided by the logarithm of  $1 +$  the market value of shares outstanding on days  $t - 1$  to  $t + 1$ , and expected trading volume uses a similar ratio for the total market volume adjusted with coefficients from a regression of the firm's actual trading volume on the total market volume for the 100 trading days (after excluding three-day windows around prior quarterly announcements) immediately preceding day  $t - 1$ .  $\Delta P_d$  is the volume-weighted price change over  $n$  trading days immediately preceding day  $t - 2$ ,  $(1/248) (dVOL_{t-n} / \sum_{m=3}^{500} dVOL_{t-m}) \Delta P_{t-n} / \sqrt{n - 2}$ , where  $\Delta P_{t-n}$  is equal to the logarithm of the stock price on day  $t - 2$  (adjusted for stock splits and stock dividends) minus the logarithm of the stock price on day  $t - n$ ,  $dVOL_{t-n}$  is the daily trading volume on day  $t - n$ ,  $\sum_{m=3}^{500} dVOL_{t-m}$  is the total trading volume over the two years immediately preceding day  $t - 2$ , and  $\sqrt{n - 2}$  is a scaling factor to minimize heteroscedasticity in price changes computed across different holding periods.  $ITD_d$  is equal to the product of  $\Delta RATE$  and  $\Delta P_d$ , where  $\Delta RATE$  is the maximum statutory short-term capital gains tax rate minus the maximum statutory long-term capital gains tax rate on day  $t$ . Duration,  $d$ , is the number of trading days from the quarterly earnings announcement date,  $t$ , that an investor, which purchased shares on day  $t - n$ , must hold the stock to meet the requisite ITD holding period of 250 trading days.  $INTENSITY$  is the the variance of daily changes in the logarithm of stock price estimated over the 100 trading days immediately preceding day  $t - 1$  expressed as a sample rank (high rank is equivalent to high variance). Other *controls* (defined in Section 3.2) include *AUE*, *NONLINEAR*, *SIZE*, *LPRIOR\_DISP*, *NUM\_EST*, and *NASDAQ*. Coefficient  $t$ -statistics are based on standard errors adjusted for clustering at the firm level.

**Table 7**  
**MIDAS Regression Examining the Intensity of Risk and**  
**Trading Volume Around Quarterly Earnings Announcements**  
**for Appreciated and Depreciated Holding Periods**

Selected MIDAS Parameters		Pred.	Dependent Variable: <i>AVOL</i>	
			Coeff.	( <i>t</i> -stat)
<i>ITD</i> <sub><i>d</i></sub>	$\gamma_0^A \times 10^{-2}$	(-)	-2.035	(-7.89)
	$\gamma_1^A$	(+)	1.423	(3.45)
	$\gamma_2^A \times 10^3$		-2.410	(-1.73)
	$\gamma_{int}^A \times 10^4$	(+)	3.732	(2.69)
	$\gamma_0^D \times 10^{-2}$	(-)	2.560	(0.45)
	$\gamma_1^D$	(+)	-0.045	(-0.09)
	$\gamma_2^D \times 10^3$		3.289	(1.84)
	$\gamma_{int}^D \times 10^4$	(+)	0.561	(1.02)

Adjusted  $R^2 = 0.091$

This table presents selected parameter estimates from the following Mixed Data Sampling (MIDAS) regression:

$$AVOL = \beta_0 + \sum_{d=1}^{248} \beta_{\Delta P}(\theta) \cdot \Delta P_d + \sum_{d=1}^{248} \beta_{ITD}(\theta) \cdot ITD_d + controls + \epsilon,$$

$$\begin{aligned} \text{subject to: } \beta_{\Delta P}(\theta) &= APP_d \cdot (\alpha_0^A + \alpha_1^A \cdot d + \alpha_2^A \cdot d^2 + \alpha_{int}^A \cdot INTENSITY) \\ &\quad + DEP_d \cdot (\alpha_0^D + \alpha_1^D \cdot d + \alpha_2^D \cdot d^2 + \alpha_{int}^D \cdot INTENSITY), \\ \beta_{ITD}(\theta) &= APP_d \cdot (\gamma_0^A + \gamma_1^A \cdot d + \gamma_2^A \cdot d^2 + \gamma_{int}^A \cdot INTENSITY) \\ &\quad + DEP_d \cdot (\gamma_0^D + \gamma_1^D \cdot d + \gamma_2^D \cdot d^2 + \gamma_{int}^D \cdot INTENSITY) \end{aligned}$$

where  $\theta \in \{d, INTENSITY, APP_d, DEP_d\}$ . The dependent variable is the three-day abnormal trading volume, *AVOL* (defined in Section 3.2), around 67,493 quarterly earnings announcements from 1982 to 2005.  $\Delta P_d$  is the volume-weighted price change over  $n$  trading days immediately preceding day  $t - 2$ ,  $(1/248)(dVOL_{t-n} / \sum_{m=3}^{500} dVOL_{t-m}) \Delta P_{t-n} / \sqrt{n-2}$ , where  $\Delta P_{t-n}$  is equal to the logarithm of the stock price on day  $t - 2$  (adjusted for stock splits and stock dividends) minus the logarithm of the stock price on day  $t - n$ ,  $dVOL_{t-n}$  is the daily trading volume on day  $t - n$ ,  $\sum_{m=3}^{500} dVOL_{t-m}$  is the total trading volume over the two years immediately preceding day  $t - 2$ , and  $\sqrt{n-2}$  is a scaling factor to minimize heteroscedasticity in price changes computed across different holding periods.  $ITD_d$  is equal to the product of  $\Delta RATE$  and  $\Delta P_d$ , where  $\Delta RATE$  is the maximum statutory short-term capital gains tax rate minus the maximum statutory long-term capital gains tax rate on day  $t$ . Duration,  $d$ , is the number of trading days from the quarterly earnings announcement date,  $t$ , that an investor, which purchased shares on day  $t - n$ , must hold the stock to meet the requisite ITD holding period of 250 trading days. *INTENSITY* is the the variance of daily changes in the logarithm of stock price estimated over the 100 trading days immediately preceding day  $t - 1$  expressed as a sample rank (high rank is equivalent to high variance).  $APP_d$  is an indicator variable equal to one if the change in stock price for an investor with duration,  $d$ , is positive (i.e.  $\Delta P_d > 0$ ) and equal to zero otherwise.  $DEP_d$  is an indicator variable equal to one if the change in stock price for an investor with duration,  $d$ , is not positive (i.e.  $\Delta P_d \leq 0$ ) and equal to zero otherwise. Other *controls* (defined in Section 3.2) include *AUE*, *NONLINEAR*, *SIZE*, *LPRIOR\_DISP*, *NUM\_EST*, and *NASDAQ*. Coefficient *t*-statistics are based on standard errors adjusted for clustering at the firm level.

Table 8

**MIDAS Regression Examining Alternative Measures of Risk and Trading Volume Around Quarterly Earnings Announcements**

Selected MIDAS Parameters		Dependent Variable: <i>AVOL</i>					
		(1)		(2)		(3)	
		Coeff.	( <i>t</i> -stat)	Coeff.	( <i>t</i> -stat)	Coeff.	( <i>t</i> -stat)
<i>ITD</i> <sub><i>d</i></sub>	$\gamma_0^A \times 10^{-2}$	-2.041	(-8.01)	-1.904	(-7.71)	-2.029	(-7.76)
	$\gamma_1^A$	1.399	(2.75)	1.041	(2.61)	1.392	(2.59)
	$\gamma_2^A \times 10^3$	-1.670	(-1.29)	-1.534	(-1.13)	-1.830	(-1.43)
	$\gamma_{idio}^A \times 10^4$	4.157	(2.24)			3.451	(2.51)
	$\gamma_{syst}^A \times 10^4$	-0.837	(-0.93)			-1.435	(-1.07)
	$\gamma_{skew}^A \times 10^4$			0.711	(1.52)		
	$\gamma_{inst}^A \times 10^4$					0.623	(0.21)

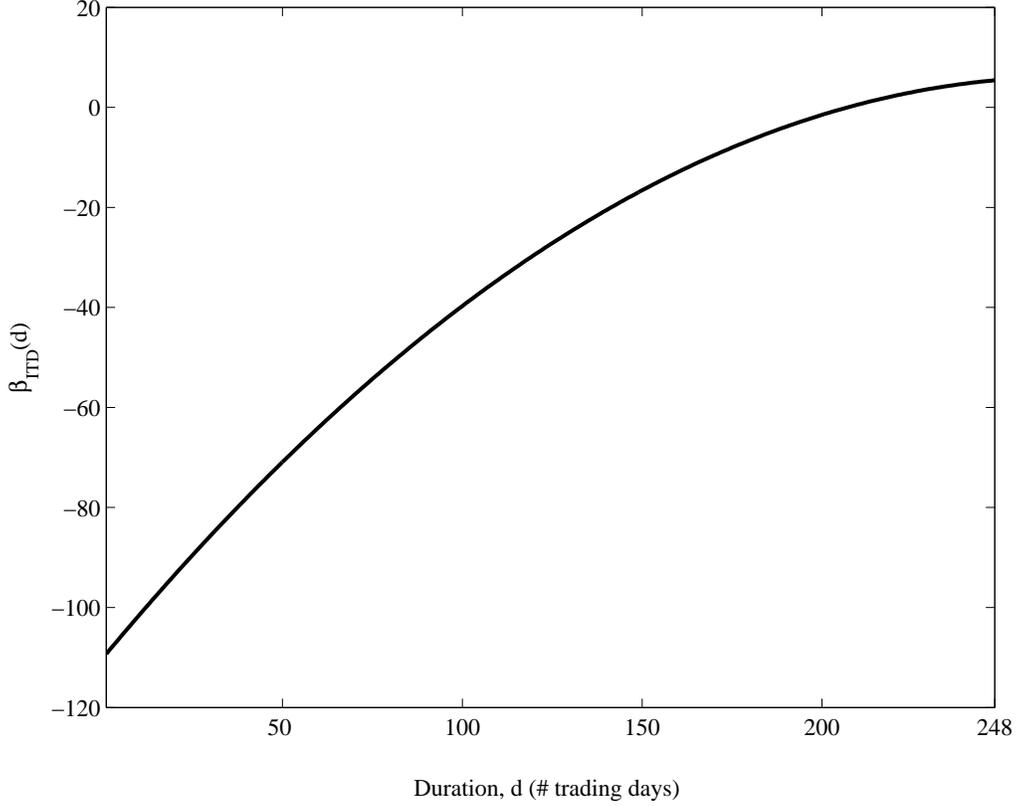
This table presents selected parameter estimates from the following MIXed DATA Sampling (MIDAS) regression:

$$AVOL = \beta_0 + \sum_{d=1}^{248} \beta_{\Delta P}(\theta) \cdot \Delta P_d + \sum_{d=1}^{248} \beta_{ITD}(\theta) \cdot ITD_d + controls + \epsilon,$$

$$\begin{aligned} \text{subject to: } \beta_{\Delta P}(\theta) &= APP_d \cdot (\alpha_0^A + \alpha_1^A \cdot d + \alpha_2^A \cdot d^2 + \alpha_{idio}^A \cdot IDIO + \alpha_{syst}^A \cdot SYST \\ &\quad + \alpha_{skew}^A \cdot SKEW + \alpha_{inst}^A \cdot INST) \\ &\quad + DEP_d \cdot (\alpha_0^D + \alpha_1^D \cdot d + \alpha_2^D \cdot d^2 + \alpha_{idio}^D \cdot IDIO + \alpha_{syst}^D \cdot SYST \\ &\quad + \alpha_{skew}^D \cdot SKEW + \alpha_{inst}^D \cdot INST), \\ \beta_{ITD}(\theta) &= APP_d \cdot (\gamma_0^A + \gamma_1^A \cdot d + \gamma_2^A \cdot d^2 + \gamma_{idio}^A \cdot IDIO + \gamma_{syst}^A \cdot SYST \\ &\quad + \gamma_{skew}^A \cdot SKEW + \gamma_{inst}^A \cdot INST) \\ &\quad + DEP_d \cdot (\gamma_0^D + \gamma_1^D \cdot d + \gamma_2^D \cdot d^2 + \gamma_{idio}^D \cdot IDIO + \gamma_{syst}^D \cdot SYST \\ &\quad + \gamma_{skew}^D \cdot SKEW + \gamma_{inst}^D \cdot INST), \end{aligned}$$

where  $\theta \in \{d, IDIO, SYST, SKEW, INST, APP_d, DEP_d\}$ . The dependent variable is the three-day abnormal trading volume, *AVOL* (defined in Section 3.2), around 67,493 quarterly earnings announcements from 1982 to 2005.  $\Delta P_d$  is the volume-weighted price change over  $n$  trading days immediately preceding day  $t - 2$ ,  $(1/248) (dVOL_{t-n} / \sum_{m=3}^{500} dVOL_{t-m}) \Delta P_{t-n} / \sqrt{n-2}$ , where  $\Delta P_{t-n}$  is equal to the logarithm of the stock price on day  $t - 2$  (adjusted for stock splits and stock dividends) minus the logarithm of the stock price on day  $t - n$ ,  $dVOL_{t-n}$  is the daily trading volume on day  $t - n$ ,  $\sum_{m=3}^{500} dVOL_{t-m}$  is the total trading volume over the two years immediately preceding day  $t - 2$ , and  $\sqrt{n-2}$  is a scaling factor to minimize heteroscedasticity in price changes computed across different holding periods.  $ITD_d$  is equal to the product of  $\Delta RATE$  and  $\Delta P_d$ , where  $\Delta RATE$  is the maximum statutory short-term capital gains tax rate minus the maximum statutory long-term capital gains tax rate on day  $t$ . Duration,  $d$ , is the number of trading days from the quarterly earnings announcement date,  $t$ , that an investor, which purchased shares on day  $t - n$ , must hold the stock to meet the requisite ITD holding period of 250 trading days. *INTENSITY* is the the variance of daily changes in the logarithm of stock price estimated over the 100 trading days immediately preceding day  $t - 1$  expressed as a sample rank (high rank is equivalent to high variance). *IDIO* (*SYST*) is the residual (predicted) variance, expressed as a sample rank, from a regression of firm-specific excess returns on the excess market return and the excess 2-digit industry return estimated over the 100 trading days immediately preceding day  $t - 1$ . *SKEW*, expressed as a sample rank, is the negative coefficient of skewness of the firm-specific daily return distribution estimated over the 100 trading days immediately preceding day  $t - 1$ . *INST*, expressed as a sample rank, is the percentage of shares held by a 13-f filing institution at the end of the calendar quarter immediately preceding the earnings announcement date,  $t$ .  $APP_d$  is an indicator variable equal to one if the change in stock price for an investor with duration,  $d$ , is positive (i.e.  $\Delta P_d > 0$ ) and equal to zero otherwise.  $DEP_d$  is an indicator variable equal to one if the change in stock price for an investor with duration,  $d$ , is not positive (i.e.  $\Delta P_d \leq 0$ ) and equal to zero otherwise. Other *controls* (defined in Section 3.2) include *AUE*, *NONLINEAR*, *SIZE*, *LPRIOR\_DISP*, *NUM\_EST*, and *NASDAQ*. Coefficient *t*-statistics are based on standard errors adjusted for clustering at the firm level.

**Figure 1**  
**Sensitivity of Trading Volume Around Quarterly Earnings**  
**Announcements to ITD Incentives as a Function of Duration,  $d$**



This figure plots the  $\beta_{ITD}(d)$  coefficient as a function of duration,  $d$ . The coefficient  $\beta_{ITD}(d)$  is estimated from the following MIDAS regression:

$$AVOL = \beta_0 + \sum_{d=1}^{248} \beta_{\Delta P}(d) \cdot \Delta P_d + \sum_{d=1}^{248} \beta_{ITD}(d) \cdot ITD_d + controls + \epsilon,$$

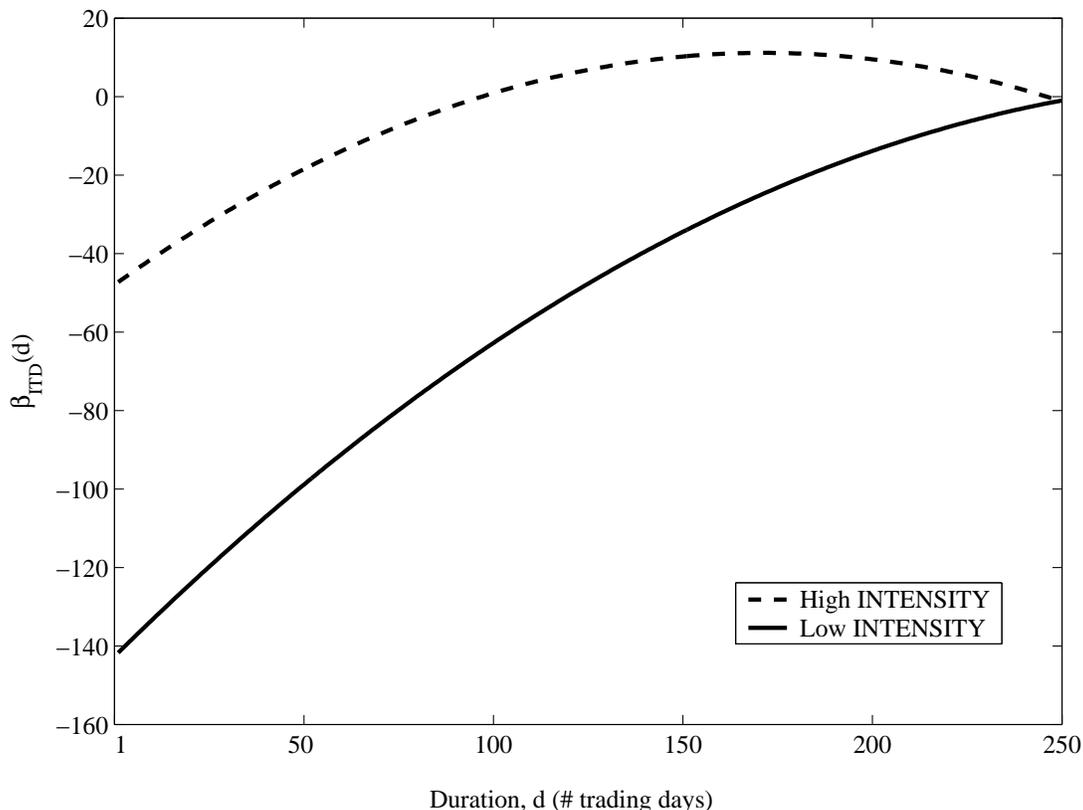
$$\text{subject to: } \beta_{\Delta P}(d) = \alpha_0 + \alpha_1 \cdot d + \alpha_2 \cdot d^2,$$

$$\beta_{ITD}(d) = \gamma_0 + \gamma_1 \cdot d + \gamma_2 \cdot d^2,$$

Let  $t$  denote the quarterly earnings announcement date identified by Compustat. The dependent variable is the three-day abnormal trading volume,  $AVOL$ , around quarterly earnings announcements from 1982 to 2005. Specifically,  $AVOL$  is 100 times the actual less expected trading volume on days  $t - 1$  to  $t + 1$ , where actual trading volume is the natural logarithm of 1 + the dollar volume on days  $t - 1$  to  $t + 1$ , divided by the logarithm of 1 + the market value of shares outstanding on days  $t - 1$  to  $t + 1$ , and expected trading volume uses a similar ratio for the total market volume adjusted with coefficients from a regression of the firm's actual trading volume on the total market volume for the 100 trading days (after excluding three-day windows around prior quarterly announcements) immediately preceding day  $t - 1$ .  $\Delta P_d$  is the volume-weighted price change over  $n$  trading days immediately preceding day  $t - 2$ ,  $(1/248) (dVOL_{t-n} / \sum_{m=3}^{500} dVOL_{t-m}) \Delta P_{t-n} / \sqrt{n-2}$ , where  $\Delta P_{t-n}$  is equal to the logarithm of the stock price on day  $t - 2$  (adjusted for stock splits and stock dividends) minus the logarithm of the stock price on day  $t - n$ ,  $dVOL_{t-n}$  is the daily trading volume on day  $t - n$ ,  $\sum_{m=3}^{500} dVOL_{t-m}$  is the total trading volume over the two years immediately preceding day  $t - 2$ , and  $\sqrt{n-2}$  is a scaling factor to minimize heteroscedasticity in price changes computed across different holding periods.  $ITD_d$  is equal to the product of  $\Delta RATE$  and  $\Delta P_d$ , where  $\Delta RATE$  is the maximum statutory short-term capital gains tax rate minus the maximum statutory long-term capital gains tax rate on day  $t$ . Duration,  $d$ , is the number of trading days from the quarterly earnings announcement date,  $t$ , that an investor, which purchased shares on day  $t - n$ , must hold the stock to meet the requisite ITD holding period of 250 trading days. Other *controls* (defined in Section 3.2) include  $AUE$ ,  $NONLINEAR$ ,  $SIZE$ ,  $LPRIOR\_DISP$ ,  $NUM\_EST$ , and  $NASDAQ$ .

Figure 2

Sensitivity of Trading Volume Around Quarterly Earnings Announcements to ITD Incentives as a Function of Duration,  $d$ , Across Low and High Intensity Samples



This figure plots the  $\beta_{ITD}(d)$  coefficient as a function of *duration* for both low and high *intensity* samples. Observations are classified as low (high) *intensity* if  $\sigma_{Ret_{j,t}}$  is below (not below) the sample median.  $\sigma_{Ret_{j,t}}$  is the standard deviation of daily change in the natural logarithm of firm  $j$ 's stock price estimated over the 100 trading days immediately preceding day  $t - 1$  where  $t$  is firm  $j$ 's quarterly announcement date. *Duration*,  $d$ , is the number of trading days from  $t$  that an investor, which purchased shares on day  $t - 252 + d$ , must hold the stock to qualify for an ITD exemption. The coefficient  $\beta_{ITD}^*(d)$  is equal to  $\beta_{ITD}(d)/\sqrt{251 - d}$  where  $\beta_{ITD}(d)$  is estimated from the following MIDAS regression:

$$VOLUME = \beta_0 + \sum_{d=1}^{250} \beta_{ITD}(d) \frac{ITD(d)}{\sqrt{251 - d}} + controls + error,$$

subject to  $\beta_{ITD}(d) = \alpha_0 + \alpha_1 \cdot d + \alpha_2 \cdot d^2$ . The dependent variable,  $VOLUME_{j,t}$ , is 100 times the actual less expected trading volume on days  $t - 1$  to  $t + 1$ , where actual trading volume is the natural logarithm of  $1 +$  the dollar volume on days  $t - 1$  to  $t + 1$ , divided by the natural logarithm of  $1 +$  the market value of shares outstanding on days  $t - 1$  to  $t + 1$ , and expected trading volume uses a similar ratio for the total market volume adjusted with coefficients from a regression of firm  $j$ 's actual trading volume on market volume for the 100 trading days (after excluding prior 3-day quarterly announcement windows) immediately preceding day  $t - 1$ .  $ITD_{j,t}(d)$  is equal to the product of  $\Delta RATE_t$  and  $\Delta P_{j,t}(d)$ .  $\Delta RATE_t$  is the maximum statutory short-term capital gains tax rate minus the maximum statutory long-term capital gains tax rate on day  $t$ .  $\Delta P_{j,t}(d)$  is firm  $j$ 's volume-weighted, total price change over the prior  $251 - d$  trading days immediately preceding day  $t - 2$ ,  $(DVOL_{t-252+d} / \sum_{n=1}^{500} DVOL_{t-2-n}) \Delta P_{t-252+d}$ , where  $\Delta P_{t-252+d}$  is equal to the natural logarithm of the stock price on day  $t - 2$  (adjusted for stock splits and stock dividends) minus the natural logarithm of the stock price on day  $t - 252 + d$ ,  $DVOL_{t-252+d}$  is the daily trading volume on day  $t - 252 + d$ , and  $\sum_{n=1}^{500} DVOL_{t-2-n}$  is the total trading volume over the 500 trading days (approximately 2 years) immediately preceding day  $t - 2$ .